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AUGMENTED REALITY SYSTEM FOR REHABILITATION: NEW APPROACH BASED ON HUMAN INTERACTION AND BIOFEEDBACK

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Certificate of Original Authorship

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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List of Abbreviations

3-D	Three Dimensional
AABB	Axis-Aligned Bounding Box
AD	Anterior Deltoid
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
APTA	American Physical Therapy Association
AR	Augmented Reality
ARIS	AR based Illusion System
BB	Biceps Brachii
BCR	Balloon Collection Rehabilitation
BPNN	Back Propagation Neural Network
BV	Bounding Volumes
CIMT	Constraint Induced Movement Therapy
CMR	Circular Motion Rehabilitation
CNS	Central Nervous System
CPM	Continuous Passive Motion
CT	Computed Tomography
CVA	Cerebrovascular Accident
D-H	Denavit-Hartenberg
DOF	Degree of Freedom
DOPs	Discrete Orientation Polytopes
EE	Elbow Extension
EF	Elbow Flexion

ELM	Extreme Learning Machine
EMD	Electromechanical Delay
EMG	Electromyogram
FAR	Feeding Animal Rehabilitation
FK	Forward Kinematic
fMRI	Functional Magnetic Resonance Imaging
FP	Forearm Pronation
FS	Forearm Supination
IAV	Integrated Absolute Value
IK	Inverse Kinematic
IMU	Inertial Measurement Unit
IR	Inward Rotation
LE	Lower Extremity
MAV	Mean Absolute Value
MRI	Magnetic Resonance Imaging
MT	Mirror Therapy
MVC	Maximum Voluntary Contraction
MVF	Mirror Visual Feedback
NRMSE	Normalised Root Mean Squared Error
OBB	Oriented Bounding Box
OR	Outward Rotation
PD	Posterior Deltoid
PM	Pectoralis Major
PNS	Peripheral Nervous System
PPR	Ping Pong Rehabilitation
PV3D	Papervision3D
RE	Real Environment
RF	Radial Flexion
RGB	Red, Green, Blue
RHI	Rubber Hand Illusion
ROM	Range of Motion
SAB	Shoulder Abduction

SAD	Shoulder Adduction
SCI	Spinal Cord Injury
SE	Shoulder Extension
SEC	Series Elastic Component
sEMG	Surface Electromyography
SF	Shoulder Flexion
SHE	Shoulder Hyperextension
SLFNs	Single-hidden Layer Feedforward Networks
SSLs	Sphere Swept Lines
SSPs	Sphere Swept Points
SSRs	Sphere Swept Rectangles
TBI	Traumatic Brain Injury
TDF	Time Domain Feature
TIA	Transient Ischemic Attack
TMS	Transcranial Magnetic Simulation
TOR	Transfer Object Rehabilitation
TOT	Task Oriented Therapy
UDP	Universal Datagram Protocol
UE	Upper Extremity
UF	Ulnar Flexion
VAR	Variance
VE	Virtual Environment
VHA	Virtual Human Arm
WA	Willison Amplitude
WE	Wrist Extension
WF	Wrist Flexion
WHE	Wrist Hypertension
WL	Waveform Length
ZC	Zero Crossing

Abstract

Rehabilitation is the process of training for someone in order to recover or improve their lost functions caused by neurological deficits. The upper limb rehabilitation system provides relearning of motor skills that are lost due to any neurological injuries via motor rehabilitation training. The process of motor rehabilitation is a form of motor learning via practice or experience. It requires thorough understanding and examination of neural processes involved in producing movement and learning as well as the medical aspects that may affect the central nervous system (CNS) or peripheral nervous system (PNS) in order to develop an effective treatment system. Although there are numerous rehabilitation systems which have been proposed in literatures, a low cost upper limb rehabilitation system that maximizes the functional recovery by stimulating the neural plasticity is not widely available. This is due to lack of motivation during rehabilitation training, lack of real time biofeedback information with complete database, the requirement of one to one attention between physiotherapist and patient, the technique to stimulate human neural plasticity.

Therefore, the main objective of this thesis is to develop a novel low cost rehabilitation system that helps recovery not only from loss of physical functions, but also from loss of cognitive functions to fulfill the aforementioned gaps via multimodal technologies such as augmented reality (AR), computer vision and signal processing. In order to fulfill such ambitious objectives, the following contributions have been implemented.

Firstly, since improvements in physical functions are targeted, the ***Reha***bilitation system with ***Bio***feedback simulation (RehaBio) is developed. The system enhances user's motivation via game based therapeutic exercises and biofeedback. For this, AR based therapeutic games are developed to provide eye-hand coordination with inspiration in

motivation via immediate audio and visual feedback. All the exercises in RehaBio are developed in a safe training environment for paralyzed patients. In addition to that, real-time biofeedback simulation is developed and integrated to serve in two ways: (1) from the patient's point of view, the biofeedback simulation motivates the user to execute the movements since it will animate the different muscles in different colors, and (2) from the therapist's point of view, the muscle simulations and EMG threshold level can be evaluated as patient's muscle performance throughout the rehabilitation process.

Secondly, a new technique that stimulates the human neural plasticity is proposed. This is a virtual human arm (VHA) model that driven by proposed continuous joint angle prediction in real time based on human biological signal, Electromyogram (EMG). The VHA model simulation aims to create the illusion environment in Augmented Reality-based Illusion System (ARIS).

Finally, a complete novel upper limb rehabilitation system, Augmented Reality-based Illusion System (ARIS) is developed. The system incorporates some of the developments in RehaBio and real time VHA model to develop the illusion environment. By conducting the rehabilitation training with ARIS, user's neural plasticity will be stimulated to re-establish the neural pathways and synapses that are able to control mobility. This is achieved via an illusion concept where an illusion scene is created in AR environment to remove the impaired real arm virtually and replace it with VHA model to be perceived as part of the user's own body. The job of the VHA model in ARIS is when the real arm cannot perform the required task, it will take over the job of the real one and will let the user perceive the sense that the user is still able to perform the reaching movement by their own effort to the destination point. Integration with AR based therapeutic exercises and motivated immediate intrinsic and extrinsic feedback in ARIS leads to serve as a novel upper limb rehabilitation system in a clinical setting.

The usability tests and verification process of the proposed systems are conducted and provided with very encouraging results. Furthermore, the developments have been demonstrated to the clinical experts in the rehabilitation field at Port Kembla Hospital. The feedback from the professionals is very positive for both the RehaBio and ARIS systems and they have been recommended to be used in the clinical setting for paralyzed patients.

Chapter 1
Introduction

Functional limitation or paralysis refers to loss of muscle function for one or more muscles in part of the body. This is most often caused by damage in the nervous system: central nervous system (CNS) or peripheral nervous system (PNS) which is the way passes the messages pass between the brain and muscles. This damage may be due to traumatic brain injury (TBI), spinal cord injury (SCI), cerebrovascular accident (CVA) or any other neurological disorders. The paralysis can be either localised or generalised where the former affects a particular part of the body while the latter affects a wider area depending on which level of the nervous system is damaged. This limitation has effects in three domains of function: physical, psychological, and social as depicted in Figure 1.1 (adopted from [1]). Physical function is the intended focus of most physical rehabilitation assessments and interventions. Although physical rehabilitation professionals focus primarily on physical functioning, researchers from [1] appropriately points out that rehabilitation impacts on all three domains. In order to recover from physical loss functions and to improve quality of life, the "Physical Therapies" or "Rehabilitation Therapies" are conducted in rehabilitation care. The main purpose of rehabilitation is aimed to improve, maintain or restore physical strength, cognition and mobility with optimal results and a return to normal social life. To facilitate the maximum recovery outcomes, diverse teams of clinical experts blend many specialties for the best rehabilitation treatment plan such as

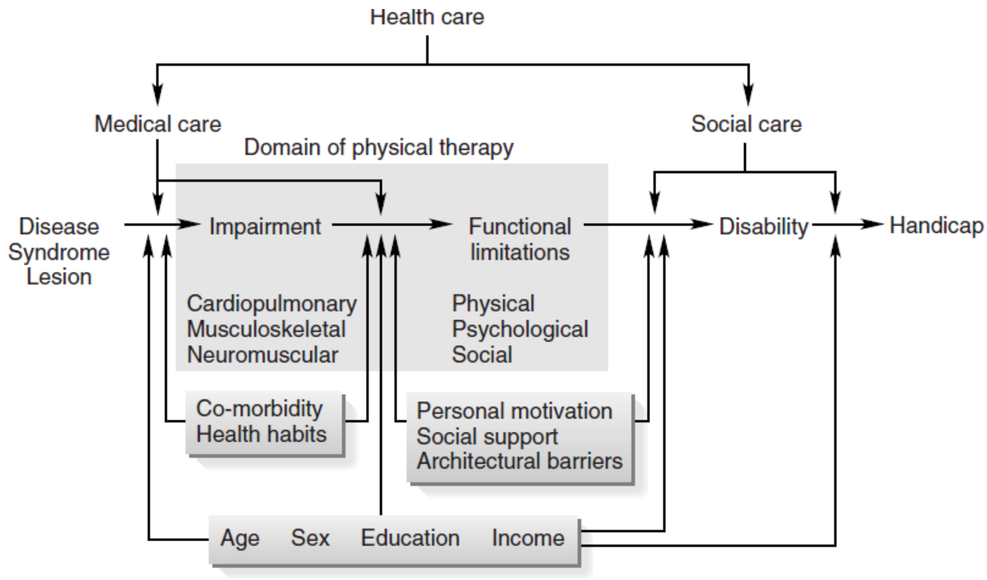


Figure 1-1 Healthcare Continuum from Disease to Handicap

physical therapy for increased strength and mobility, occupational therapy for improved daily life skills and cognitive functions and so forth.

This chapter covers a basic background on physical rehabilitation technique for any neurological disabilities by means of traditional approach and technology approach. This background provides the reader with the foundation for further knowledge of an effective rehabilitation system with advanced technology. To this end, three main areas are carefully reviewed to provide effective and rapid recovery from limitation of upper limb movements. The review analyses the merits and deficiencies of these areas to enhance the best recovery outcome for paralyzed patients, which ultimately form the research objectives for this thesis. In this chapter, the structure of the thesis is also outlined to simplify the reading and understanding.

1.1. Background

In order to provide the best rehabilitation treatment for paralysis patients due to any neurological deficits, American Physical Therapy Association APTA proposes a patient management cycle [2] involving ***Examination***, ***Evaluation***, ***Diagnosis***, ***Prognosis***, ***Intervention*** elements for the physical rehabilitation process. ***Examination*** is the very first element in rehabilitation process to collect data such as intensity of muscle strength, limitation level in range of motion and ability of functional activities. After the initial examination, the collected data are then organized and analyzed in ***Evaluation*** element to identify the causative factors. Based on the process and end result of evaluating examination data, physical therapists organize into clusters, syndromes or categories in ***Diagnosis*** element. After a thorough analysis of data in ***Diagnosis*** element has been evaluated, suitable timing and frequency of the interventions to reach the optimal level of improvement is defined in ***Prognosis*** element. The ***Intervention*** is the physical therapy procedures which include coordination, communication, restorative interventions, compensatory interventions and preventative interventions which are chosen based on the evaluation of the examination, medical and physical therapy diagnosis, prognosis, anticipated goals and expected outcomes. The outputs from the ***Intervention*** are evaluated for efficacy of treatment. Reexamination of the patient is ongoing and involves continuous checking toward anticipated goals basedt on the outputs of ***Intervention***. If the patient attains the desired level of competence, discharge is considered. If the patient fails to achieve the stated outcomes, the therapist must determine the reasons and modifications are sought until the desired goal is achieved. Therefore, the design of the ***Intervention*** plays a major role in the rehabilitation process along with the requirements of individual condition. The intervention can be manual based physical therapy or technology based physical therapy. In the context of manual based therapy or traditional therapy, rehabilitation exercises are provided by physiotherapist with one-to-one attention between therapist and patient. This practice leads to exhaust the physiotherapist in the long run. In addition to this, ongoing rehabilitation costs and labor costs are too high for the patients and their families all over the world.

In Australia, 4.2 million or 18.5% of Australians are living with disability in 2012 according to the Australian Bureau of Statistics [3]. Among those people with disability, 3.7 million (88%) had a specific limitation or restriction that has an effect on mobility, daily live activities, communication or limits social and community participation. Among these 3.7 million, only 184,700 disable people are living in cared-accommodation. Furthermore, the rest of the people with disability are living in private and non-private dwellings without the help from professionals. This can be due to the lack of local rehabilitation facilities or patients are unable to travel to rehabilitation facilities. However, one of the main reasons for this is the “Cost” of caring. Based on the Deloitte Assess Economics calculations [4], the estimated cost of disability in Australia for each individual is almost 130,000 AUD which is very expensive and become a burden for the patients and their families. According to the physiotherapy registrant data in 2012 [5], there are a total of 24,304 physiotherapists in Australia. This is almost 8:1 (patients: physiotherapist) ratio in cared-accommodation and obviously there is a high chance of fatigue for physiotherapists in the long run. Therefore, the ***shortage of rehabilitation therapists*** in rehabilitation sectors is one of the major shortfalls in Australia. In addition to this, repetitive traditional rehabilitation exercises lead easily to ***bore and demotivate*** in long term rehabilitation training.

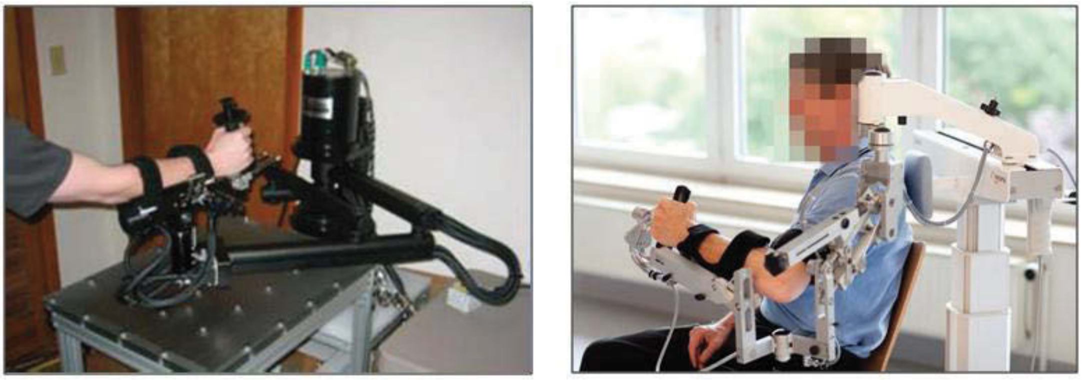
Due to these limitations, technology based physical rehabilitation therapy becomes a favourable option. Employing the technology in rehabilitation provides several advantages as follows. In the environment in which labor costs continue to rise and the costs of technology are falling, employing technology will certainly be cost-effective in the long run. Moreover, only technologically based therapies are able to provide motivated exercises repetitively without risking therapist fatigue. In addition to this, only technology based rehabilitation treatment is able to stimulate brain plasticity for fast recovery of motor functions. Therefore, the aim of this thesis is to develop technology based rehabilitation system that it will close the gap of current shortfalls such as high cost, shortage of manpower and boring traditional rehabilitation exercises.

1.2. Technology based Rehabilitation Systems

In terms of technology based rehabilitation therapy, rehabilitation robotic systems, Virtual Reality (VR) systems and Augmented Reality (AR) systems have been proposed as innovative technologies that significantly contribute in physical rehabilitation. These technologies contribute in the rehabilitation area not only to enhance the quality, consistency, and documentation of the care received, but also to extend the reach of medical rehabilitation service to remote areas so that every disabled person is able to receive effective rehabilitation care.

1.2.1. Robotic Systems

The very first conference on medical manipulators was presented in 1978 at Rocquencourt, France [6] by specialists from all over the world. This was where industry robots merged in the medical field. Since then, they have been grown significantly as assistive devices or rehabilitation robots in the rehabilitation field. The use of robots in rehabilitation has been proposed as a labor-saving approach for the provision of physiotherapy. Strictly speaking, a rehabilitation robot is not intended to replace the mechanical function of weak or missing human limbs; instead it is integrated into the rehabilitation field to enhance in restoration of lost functions. It can enhance rehabilitation exercises provided under direct guidance by



(a) End-effector system (b) Exoskeleton system

Figure 1-2: Rehabilitation Robotic Systems

a physiotherapist. The robot can be interactive and alter the therapy provided based on patient's immediate reaction or response to treatment over time such as movement pattern, number of repetitions, the forces exerted by the robot. Hence, it can provide more consistent results to achieve the ultimate goals of the treatment. In the context of rehabilitation, robotic devices can be conceived as (1) fixed-based or end-effector systems [7] and as (2) exoskeleton systems [8] as depicted in Figure 1.2. It is suggested that for the limb segment movements requiring less than 45 degrees, end-effector system appear more appropriate while larger joint excursions are more suitable with exoskeleton. And whenever a portable solution is expected, exoskeletal structures are likely more convenient than end-effector systems. In any case, both of the systems have close physical interaction with human user through smart sensors, actuators, algorithms and control strategies to detect the complex human expressions or physiological phenomena and translate this information as commands for the rehabilitation robot. This information is crucial to identify a good rehabilitation robot for both clinician and patients. The notable evidence based rehabilitation robot systems that are currently available in the market and rehabilitation care for upper limb are InMotion Arm, InMotion Wrist and InMotion Hand [9] which are clinical version of MIT-manus [10]and ArmeoPower and ArmeoSpring [8] which are clinical version of the ARMin rehabilitation robot [11].

1.2.2. Virtual Reality Systems

From 1980s, Jaron Lanier [12] first introduced "Virtual Reality" and become popular and started to employ VR in many applications. VR is a human-computer interface technology that permits the user to experience and interact within a virtual environment (VE) and experience it as if it were happening in real environment (RE). VE is the artificial environment that has developed with special software for the user to immerse and operate within this environment. It provides an easy, powerful, intuitive way of human-computer interaction through the use of goggles, gloves, body suits or headsets. The user can see and manipulate the simulated environment in the same way that works in the real world. The very first attempt of VR application was when it was employed as a visualization tool for an architect [13]. Since then, VR became more and more popular and has been widely used for many other applications such as healthcare, education, military, entertainment and so forth. Among these applications, healthcare is one of the biggest areas that employ VR technology to encompass the treatment, training, robotic surgery and simulation due to its safe environment and motivation. In the context of rehabilitation, VR systems have proven that they provide motivating training that can be superior to the training in the real world due to enriched environments, highly functional and task-oriented practice environments that are normally limited to the actual training environment[14] . In additional to this, VR can be employed to create different types of therapeutic environment specifically to a particular disability and different types of feedback. Moreover, it can also be used for setting up an automatic schedule for training, testing and recording the user's motor performances. Based on these advantages, researchers have integrated VR in rehabilitation robotics to provide a better rehabilitation platform. To create the VR environment, it requires additional hardware devices other than personal desktop system such as head-mounted display (HMD) or projector, tracker, manipulation device (three-dimensional mouse or data glove) as shown in Figure 1.3 (adopted from [15]). The examples of VR system for upper limb rehabilitation are portrayed in Figure 1.4 (adopted from [16]). However, the interactive devices that are required to be worn by the user in VR system

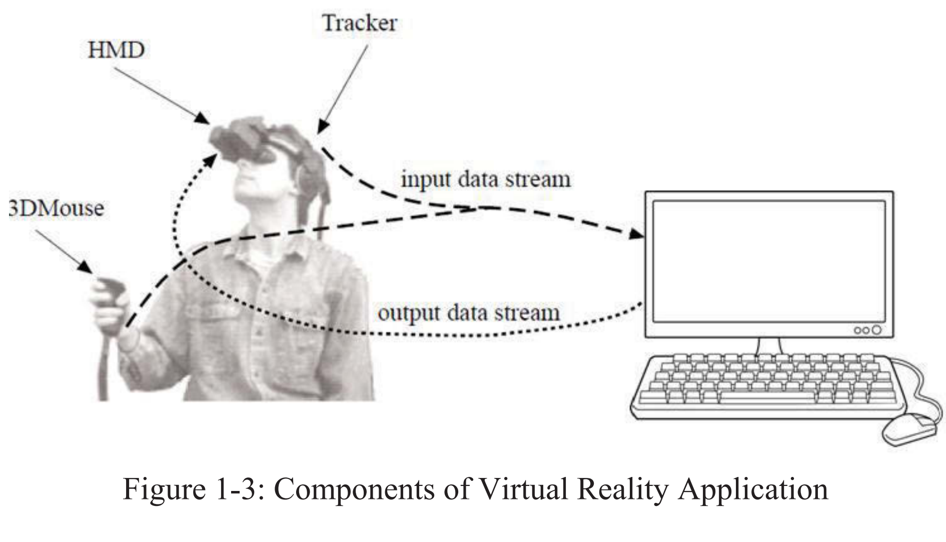


Figure 1-3: Components of Virtual Reality Application

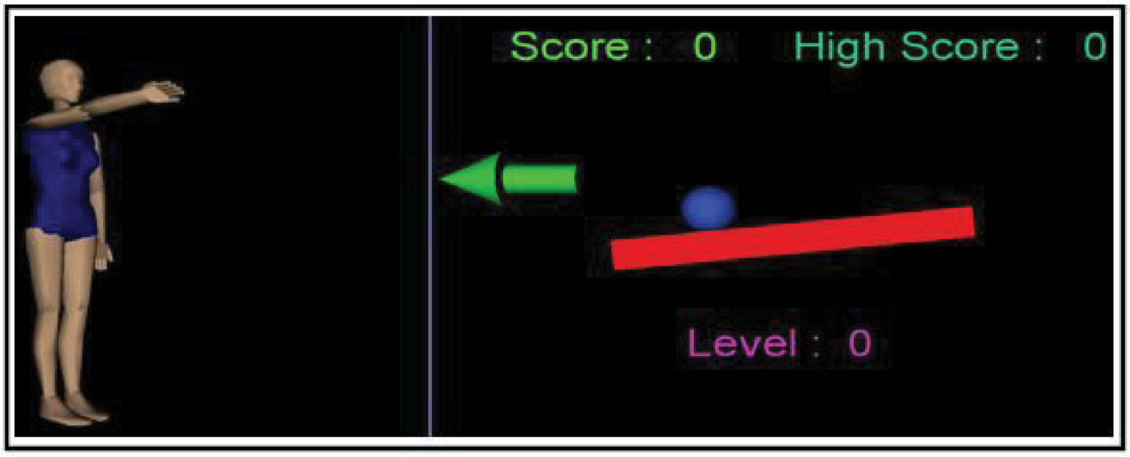


Figure 1-4: Virtual Reality based Upper Limb Rehabilitation Exercise

leads to one of the major issues in rehabilitation therapy. The limitations include:

1) Device weight that affects on paralyzed patients especially when worn on an impaired limb.
2) Fully immersive environment in HMD may lead to dangerous prone mobility in real environment.
3) Lack of feeling of "presence" due to being immersed in a computer generated environment.
4) The requirement of mapping the movements of real arm/hand to the movement of the avatars in VE.

Therefore, researchers were looking for a new technology that could provide a safe training environment yet be able to provide the same or better motivations and benefits as VR for rehabilitation therapy. This new technology is termed as "Augmented Reality", AR.

1.2.3. Augmented Reality Systems

AR is a combination of real world and virtual world where virtual objects lay on top of the real world objects. In other words, AR allows the overlay of digital information on the physical world where you "remain" as shown in Figure 1.5 (adopted from [17]). The interaction of the AR experience is in real-time without the need of any interactive devices as in VE. One of the first works on AR started at Boeing in 1990 and another work occurred in 1992 for the US air force [18]. In late 1990's Hirokazu Kato released AR toolkit to develop AR systems and this is when researchers begun to employ AR in various

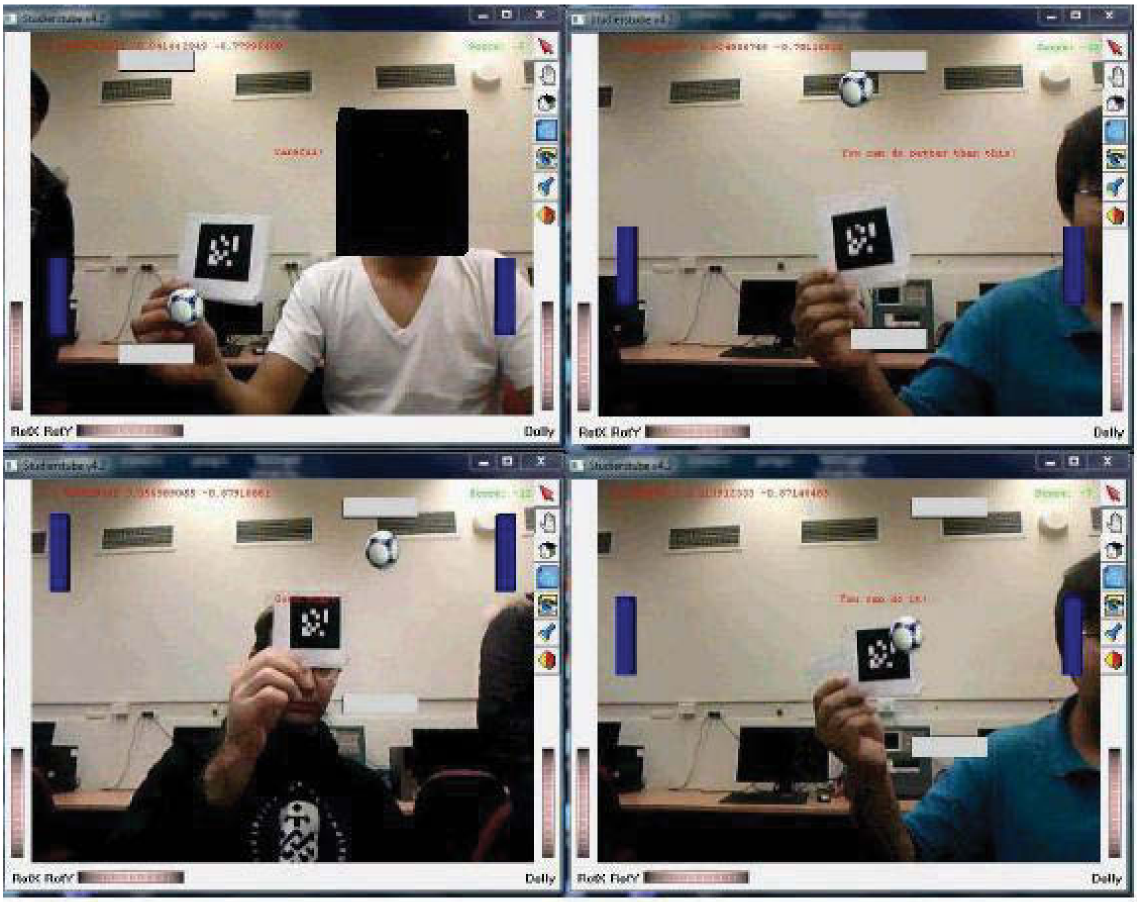


Figure 1-5: Augmented Reality based Upper Limb Rehabilitation Exercise

applications [19]. Although AR is still in the exploratory stage in many applications including the rehabilitation field, it provides additional advantages such as the user can view the real world and real objects can be employed as stimuli for the therapy. In additional to this, as a rehabilitation therapy, the physical movements for treatment and interacting activities are able to be kept consistent in AR environment. Since the research in AR rehabilitation application is relatively new, there is room for improvement in several areas such as display, depth perception and trackers to become more accurate, lighter, cheaper, and less power consuming.

1.2.4. Feedback in Rehabilitation System

The role of feedback in rehabilitation therapy is vital to promote motor learning. Feedback can be conceived as (1) intrinsic (inherent) feedback and (2) extrinsic (augmented) feedback. The former represents a natural result of the movement such as visual, vestibular and proprioception while the latter incorporates additional sensory cues that are not normally received naturally during the treatment such as visual cues, verbal cues, tactile cues and biofeedback devices. In general, feedback provides the information of initial position before the movement, error detection during the movement, and movement outcomes. In other words, feedback is monitoring posture and balance, control of slow movements or precision movements in order to maintain a desired treatment outcome. They can be represented with visual feedback, audio feedback, tactile feedback and biofeedback. In most of the rehabilitation systems, wide ranges of visual, audio and tactile feedback are employed to increase the quality of rehabilitation training. In terms of biofeedback, EMG based biofeedback is the most commonly used in motor rehabilitation as this is the self-generated biological signal that directly explains the performance of the muscles. EMG biofeedback is used for either increasing the activity in weak or paretic muscles or reduction in tone of the spastic muscles. According to the literature [20], it appears to be promising in both musculoskeletal and neurological rehabilitation although only a limited number of randomized controlled trials are reported.

1.3. Limitations of Technology based Rehabilitation Systems

Although technology based rehabilitation provides the ultimate goal of rehabilitation training which is to maximize the patient attention and effort with maximum repetitions and long term engagement. Nevertheless, there are several shortcomings with respect to this technology in rehabilitation due to the following aspects. From the clinical point of view:

- The absence of education about technological advancements and apprehensions by clinicians.
- The absence of consultation between the rehabilitation system developers (engineers) and rehabilitation professionals to provide efficient human-machine interface, user friendly, effective for specific disabilities.
- The rehabilitation professionals are uncomfortable with technology and have a fear of losing communication with patients not only in home-based rehabilitation care but also in clinical settings.

From a technology point of view:

- The funding challenges to developed technological based rehabilitation systems especially for the cost of robotic based systems.

- The lack of values and motivations to the proper treatment program that enhance movement recovery.
- The lack of feedback enhancements that not only emphasise error reduction, but also emphasise user's own kinematics.
- The lack of effectively augmenting the individual's own residual sensory perceptions into the treatment program.
- The lack of effectively stimulating to exhibit neural plasticity to recover faster from limited physical functions.

In summary, the effective therapeutic interventions based on rapid development of new technologies require a multimodal process. The knowledge sharing between clinicians and developers, efficient trained experts, usage of latent signals from individual as much as possible, enhanced motivations in treatments with real-time augmented feedback and clinical trials that demonstrate the value of near-term and future rehabilitation applications are the main ingredients to develop the successful intervention.

1.4. Objectives and Contributions

After analyzing the gaps in rehabilitation systems associated with current technologies, it is obvious that there are several gaps for a novel rehabilitation system that effectively benefits motor rehabilitation. In effort to close these gaps, the research objectives of this thesis are given as below.

- To provide a novel low cost home-based rehabilitation system that requires minimum supervision by physiotherapists.
- To create the safe training environment for paralysed patients.
- To integrate with rich biofeedback information in the novel rehabilitation system to provide higher motivation especially for long term training.
- To stimulate the human neural plasticity effectively for fast recovery in motor functions.

In order to fulfill the defined objectives, the following contributions, novel upper limb rehabilitation systems are designed and developed in order to recover faster from limited functions of upper limb. The specific research contributions for this thesis are as follows;

1. Introduce two novel rehabilitation systems namely Rehabilitation Biofeedback (RehaBio) system and Augmented Reality based Illusion System (ARIS) for upper limb rehabilitation to overcome the limitations that stated in aforementioned.
2. Develop motivated rehabilitation exercises based on AR technologies in a safe environment along with the complete database for physiotherapist. This development aims to close the gap by reducing the requirement of one to one attention between patient and therapist with different forms of eye-hand coordination, cognitive training, motivation and challenge for long term rehabilitation training. In addition to this, design a database that provides easy tracking of individual physiological data, performance history, as well as related personal information during the period of treatment. This is to reduce the manual data entry and inspection time of clinical professionals. In order to manipulate all the developed exercises, only personal computer with built in webcam and four color markers are required. Therefore, the proposed technique is very low cost and effective for every patient and even he/she can perform the rehabilitation exercises at home under professional guidance without travelling to rehabilitation hospitals or centers.
3. Develop both intrinsic and extrinsic feedback based on utilizing the EMG biofeedback in real-time. This design aims to close the current gap in lack of proper evaluation and analyzing of patient’s performance during the rehabilitation process.
4. Develop a continuous joint angle prediction model in real time via user own biosignal to simulate the developed virtual arm. This is to excite the human brain neural plasticity and provide self-motivation based on user’s latent EMG signals via novel proposed algorithm.
5. Develop a virtual arm that can be used in the illusion environment as an artificial visual feedback. The real time simulation of this visual feedback is based on user intention via EMG signal. This new technique outperform than traditional mirror therapy for rehabilitation by without needing the additional apparatus and hardware attachments to the patients.
6. Develop the complete novel upper limb rehabilitation system by integrating all of the above developments which is the ultimate goal of this thesis.

1.5. Organization of Thesis

This thesis is structured as follows;

Chapter two: Introduce the literature review about human nervous system and its possible deficits due to numerous reasons. After that, the available recovery methods through neuroplasticity were reviewed. This includes technological based rehabilitation systems, available augmenting feedbacks in terms of both intrinsic and extrinsic for better motivations and the importance of biosignal in motor rehabilitation by assessing their benefits and limitations thoroughly.

The chapters, three to five, discuss the development of a novel system that closes the current gaps in the rehabilitation field for this research, as follows:

Chapter three: Present the first contribution of this thesis represented by a novel rehabilitation system with biofeedback (RehaBio) system for upper limb rehabilitation. The proposed tracking and collision detection methods are used to employ in RehaBio exercises. The custom built upper limb rehabilitation exercises in RehaBio are allied with actual rehabilitation exercises in rehabilitation settings through value added services such as a rich supply of immediate feedback. The new method of biofeedback in RehaBio system induces self-motivation and fast recovery from limited arm articulations. The developed system is thoroughly considered and developed with ten basic principles of experience-dependent neural plasticity which detailed in Chapter 2. To assess the efficacy of the RehaBio system, the usability tests are conducted and results are evaluated by data analysis, performance analysis and questionnaire.

Chapter four: Present the second and third contribution of this thesis represented by a real time biosignal driven virtual human arm. Firstly, two machine learning based real time joint angle prediction models are proposed and one of them was selected as an optimal controller for virtual human arm (VHA) model simulation. This is to predict the user's intended motions in real time which is reflected in VHA model. Secondly, the development of VHA model in a virtual environment is detailed by mimicking the human arm articulations. The corresponding mathematical computations used to derive the VHA model are also provided. The experimental results are also reported to evaluate the effectiveness of the developed model and controller.

Chapter five: Presents the fourth contribution which is the ultimate goal of this thesis. The novel upper limb rehabilitation system named Augmented Reality-based Illusion System

(ARIS) for upper limb rehabilitation is presented in this chapter. ARIS creates the illusion scene for the patients to stimulate neural plasticity for fast recovery in both physical functions and cognitive functions via motivated exercises and enriched intrinsic and extrinsic feedback. The effectiveness of the developed system is evaluated via data analysis, performance analysis and questionnaire. In addition, the demonstration for clinical specialists in Port Kembla Hospital has been performed and the feedbacks and clinical advices have been implemented in ARIS and have made it ready for clinical trials. The demonstration of the system has been performed at Port Kembla Hospital and responses are discussed in this chapter.

Chapter six: Provides a conclusion and summary of the thesis, and suggests future directions for research.

1.6. Peer-Reviewed Publications

The contents of this thesis are based on the following papers that have been published, in-pressed, or submitted to peer-reviewed journals and conferences.

Book Chapter:

[1] Y. M. Aung and A. Al-Jumaily, "Effective Physical Rehabilitation System," in *Virtual Reality Enhanced Robot Systems for Disability Rehabilitation*, In-press, 2015.

Journal Papers:

[1] Y. M. Aung and A. Al–Jumaily, "Augmented reality–based RehaBio system for shoulder rehabilitation," *International Journal of Mechatronics and Automation,* vol. 4, pp. 52-62, 2014.

[2] Y. M. Aung and A. Al-Jumaily, "Estimation of Upper Limb Joint Angle Using SurfaceEMG Signal," *International Journal of Advanced Robotic Systems,* vol. 10, pp. 1-8, 2013.

[3] Y. M. Aung and A. Al-Jumaily, "Neuromotor Rehabilitation System with Real-Time Biofeedback," *International Journal of Computer Information Systems and Industrial Management (IJCISIM),* vol. 5, pp. 550-556, 2013.

[4] Y. M. Aung and A. Al-Jumaily, "sEMG Based ANN for Shoulder Angle Prediction," *Procedia Engineering,* vol. 41, pp. 1009-1015, 2012.*

***Best Paper Award Finalist**

Conference Papers (full paper, 4 pages or more):

[1] Y. M. Aung, K. Anam, and A. Al-Jumaily, "Continuous Prediction of Shoulder Joint Angle in Real-Time," in *7th International IEEE EMBS Neural Engineering Conference*, Montpellier, France, 2015, pp. 755-758.

[2] Y. M. Aung, A. Al-Jumaily, and K. Anam, "A Novel Upper Limb Rehabilitation System with Self-Driven Virtual Arm Illusion," in *36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Chicago, USA, 2014, pp. 3614-3617.

[3] Y. M. Aung and A. Al-Jumaily, "Real Time Biosignal-Driven Illusion System for Upper Limb Rehabilitation," in *The 11th IASTED International Conference on Biodmedical Engineering (BioMed 2014)*, Zurich, Switzerland, 2014, pp. 286-293.

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[5] Y. M. Aung and A. Al-Jumaily, "Illusion Approach for Upper Limb Motor Rehabilitation," in *International Congress on Neurotechnology, Electronics and Informatics (NEUROTECHNIX 2013)*, Vilamoura, Algarve, Portugal, 2013, pp. 99-105.

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1.7. Summary

This chapter has provided an introduction to the upper limb rehabilitation system. Among the several approaches available in rehabilitation techniques, the safest and most effective approach has been chosen and studied to implement as a novel upper limb rehabilitation system. The limitations of current rehabilitation systems have also been assessed and these limitations have inspired this doctoral research study. This research study aims to provide best rehabilitation exercises with lots of motivations, provide fast recovery via stimulation brain neural plasticity nature and making used of user’s latent EMG signals as biofeedback. These ambitious aims are implemented in two novel rehabilitation systems: the RehaBio and ARIS systems.

Chapter 2
Literature Review

2.1. Introduction

This chapter covers a basic introduction to human nervous system and related damages to the nervous system. The recovery method from these damages will be reviewed via available advanced technologies particularly for upper limb rehabilitation. Additionally, the chapter will also review the biological driven rehabilitation systems via machine learning approach. The chapter will also highlight the shortfalls in the current available systems that this research aims to overcome.

2.2. Human Nervous System

Human nervous system is made up of specialized cells called neurons. It is responsible for controlling all the biological processes and movements in the body. It consists of two main parts: Central Nervous System (CNS) and Peripheral Nervous System (PNS). CNS consists of brain and spinal cord. It is the center of the nervous system and also responsible for receiving and interpreting signals from the PNS. PNS contains nerve fibers bundled into cables called nerves which leave and enter the CNS. These can be either ***afferent*** nerves or ***efferent*** nerves. In the nervous system, afferent sensory nerves convey the information towards the CNS. In contrast, efferent motor nerves carry the signals from CNS to the cells.

The efferent fibres can be divided into the somatic nervous system and the autonomic nervous system. The somatic fibres are responsible for the voluntary movement of the body. The autonomic nervous system incorporates all the impulses that are done involuntarily, such as breathing, heartbeat etc. However this type of system can further be broken down into the sympathetic and parasympathetic systems which keep one another in check in a form of negative feedback such as the release of insulin and glucagon in sugar control in the blood. All of the actions executed by the autonomic nervous system are unconsciously done. These informational pulses executed in nervous system allow us to do our daily functions.

The anatomy of the nerve cell, neuron, consists of a nucleus situated in the cell body and a number of processes called dendrites. One process, usually much longer than the rest, is the axon or nerve fibre which carries the outgoing impulses. At the axon terminal or synaptic terminal, rapid transmission of signals occurs. The incoming signals from other neurons are conveyed via junction regions known as synapses. Synapses may be electrical or chemical. Electrical synapses make direct electrical connections between neurons. The cell that sends signals is called presynaptic and the cell that receives signals is called postsynaptic. The presynaptic area consists of large numbers of tiny spherical vessels called synaptic vesicles, neurotransmitter. When the presynaptic terminal is electrically stimulated, an array of molecules embedded in the membrane are activated, and cause the contents of the vesicles to be released into the narrow space between the presynaptic and postsynaptic membranes, called the synaptic cleft. The neurotransmitter then binds to receptors embedded in the postsynaptic membrane, causing them to enter an activated state. Depending on the type of receptor, the resulting effect on the postsynaptic cell may be excitatory, inhibitory, or modulatory in more complex ways. For instance, release of the neurotransmitter acetylcholine at a synaptic contact between a motor neuron and a muscle cell induces rapid contraction of the muscle cell. The entire synaptic transmission process takes only a fraction of a millisecond, although the effects on the postsynaptic cell may last much longer. The structure of a typical neuron is depicted in Figure 2.1 (adopted from [21]).

There are two main types of nerve fibre: the large fast conducting axons being myelinated and the small slow conducting axons being non-myelinated. The myelin sheath is a layer of phospholipids formed by glial cells (oligodendrocytes in the CNS, and Schwann cells in the PNS) that increase the conductivity of the electrical messages that are

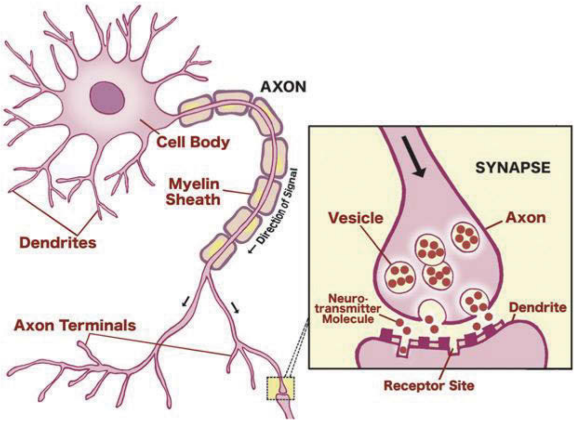


Figure 2-1: Structure of Typical Neuron

sent through the cell, which enable them to conduct impulses 50 times faster than non-myelinated fibre of the same overall diameter. Regular intermittent gaps in the myelin sheath are called nodes of Ranvier. The speed with which an axon conducts information is directly proportional to the size of the axon and the thickness of the myelin sheath [22].

In general, there are three main types of neurons which form the basic impulse-transmission pathway of the entire nervous system. These neurons include sensory neurons for sensory input such as sight, sound, feeling, etc., interneurons for integration and motor neurons for skeletal muscles, brachial muscles, cardiac muscles or smooth muscles as shown in Figure 2.2 (adopted from [23]). Sensory neurons gather information from the sensory receptors and transmit these impulses to the CNS (brain and spinal cord). The interneurons are found entirely within the CNS. They act as a link between the sensory and motor neurons. They process and integrate incoming sensory information and relay the outgoing motor information. The motor neurons transmit information from the CNS to the muscles, glands and other organs (effectors). An example of basic neural transmission pathway is illustrated in Figure 2.3 (adopted from [24]).

2.2.1. Neurological Disorder

Any injury or damage within the above mentioned nerve impulse pathway will lead to neurological disorder in which structural, biochemical or electrical abnormalities are caused in brain, spinal cord or other peripheral nerves. These abnormalities can result in range of symptoms as follows:

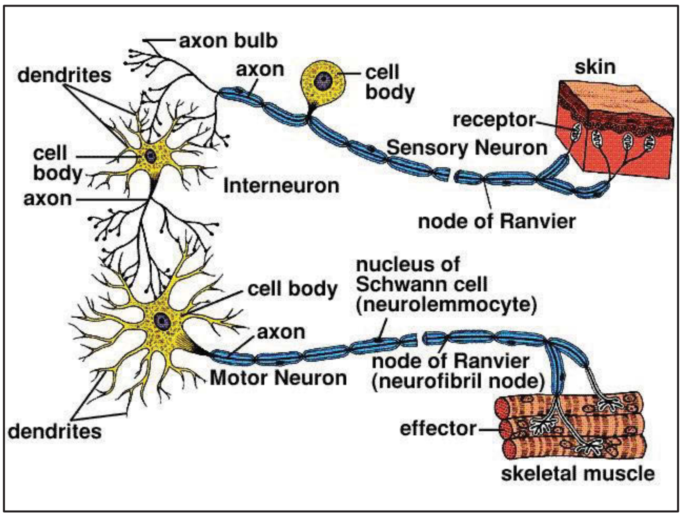


Figure 2-2: Human Nervous system

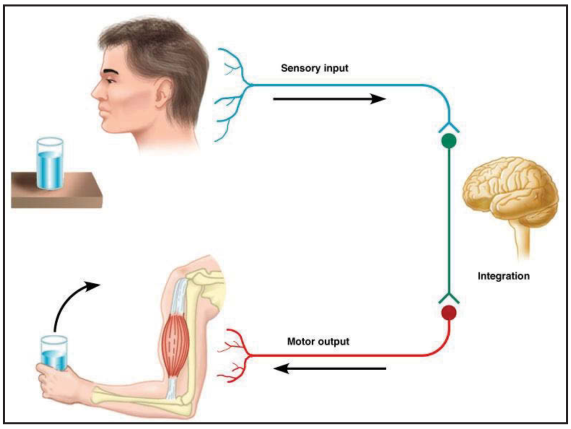


Figure 2-3: Overview of the Neurons in a Nerve Impulse Pathway

- **Paralysis or loss of muscle movement:** Due to reduced blood flow to the brain, a person can become paralyzed on one side of the body or lose certain muscle movements.
- **Memory loss or difficulty in understanding:** People who experienced stroke may suffer from some memory loss or difficulty in judgments, understanding and thinking concepts.
- **Seizures:** Abnormal electrical impulses from the brain causing convulsions.
- **Limb contractures:** Muscles become shortened in an arm or leg owing to lack of exercise or reduced range of motion.

- **Difficulty in swallowing, talking and eating:** A stroke person may experience less control over mouth and tongue movements, making it difficult to swallow, talk and eat.
- **Limb and joint pain:** It may occur due to hemiplegia or lack of mobility or exercise for a long time.
- **Depression:** People who have a stroke may become depressed and less social. They may need a caregiver for their daily activities.

These will affect the person's quality of life as well as their daily life activities. Neurological disorders can be classified into two main categories: CNS disorders and PNS disorders. The former disorders affect either the brain or spinal cord in which the damage is caused by trauma, infections, degeneration, structural defects, tumors, autoimmune disorders and stroke. The latter disorders damage the nerves due to systemic diseases, vitamin deficiency, traumatic injury, immune system disease or viral infection. Among these disorders, stroke or Cerebrovascular Accident (CVA), traumatic brain injury (TBI) and Spinal Cord Injury (SCI) are most common disorders all over the world.

2.2.1.1. Cerebrovascular Accident or Stroke

Stroke or CVA occurs due to the formation of plaque in the blood vessels. Plaque is built up of fat, cholesterol, calcium and other substances from blood. It will precipitate to the lumen of blood vessels and become thicker and harden over a period of time, and then it starts to restrict the blood flow as shown in Figure 2.4 (adopted from [25]). There are three

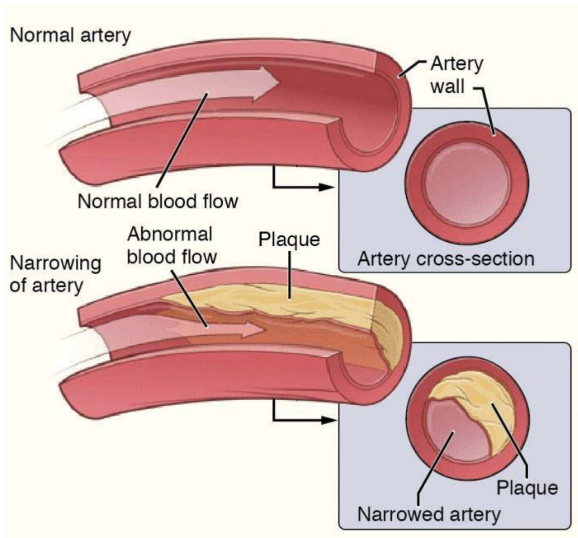
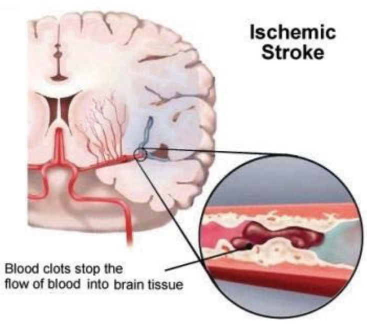


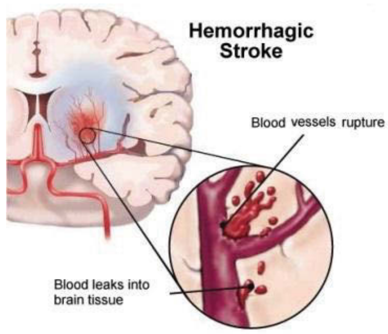
Figure 2-4: Normal Artery vs. Atherosclerotic Artery

types of stroke: (1) ischemic stroke when blood flow is interrupted by blood clot which breaks into small pieces from any part of the body and reaches the brain causing blockage to the brain blood vessels, (2) hemorrhagic stroke when the blood vessel is ruptured and fills the blood between skull and brain which causing too much pressure on the brain, and (3) transient ischemic attack (TIA) which is defined as a focal neurological deficit due to cerebral ischemia, lasting less than 24 hours. In any cases, as a result, the supply of oxygen to the brain will be disturbed causing the death of brain cells. Due to dead brain cells, some of the brain functions cannot work properly depending upon which part of the brain is damaged. The illustrations of ischemia stroke, hemorrhagic stroke and TIA are portrayed in Figure 2.5 (adopted from [26]).

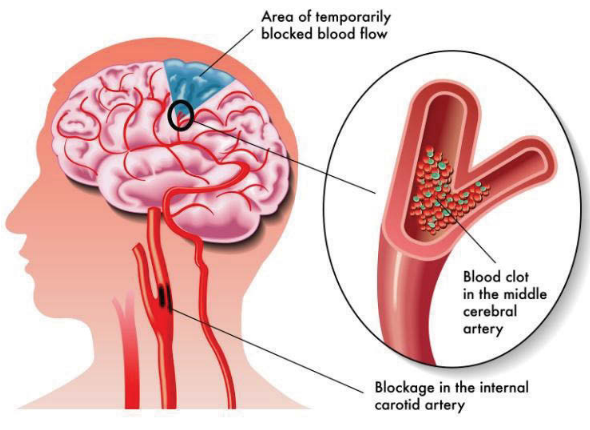
Motor impairments: Following CVA there will be some degree of paralysis from both lower and/or upper motor neuron disorders, upper motor neuron conditions usually being associated with concurrent hyperreflexia, depending on the affected location.

Cognitive dysfunctions: Cognitive dysfunction may be present with lesions involving the





(a) Ischemic stroke (b) Hemorrhagic stroke



(c) Transient Ischemic Attack

Figure 2-5: Three Types of Cerebrovascular Accident or Stroke cortex and includes impairments in alertness, attention, orientation, memory, or executive functions.

2.2.1.2. Traumatic Brain Injury

Traumatic brain injury (TBI) occurs when an external force traumatically injures the brain by sudden acceleration/deceleration within the cranium or by a complex combination of both movement and sudden impact such as vehicle accidents, violence or falls. In addition to the initial injury, it causes secondary injury which is the leading cause of inhospital deaths after TBI [27]. Most secondary brain injury is caused by brain swelling, with an increase in intracranial pressure and a subsequent decrease in cerebral perfusion leading to ischemia [28]. TBI is graded as mild, moderate, or severe on the basic of the level of consciousness after resuscitation (panel). Mild TBI is in most cases a concussion and there is full neurological recovery, although many of patients suffer short term memory and concentration difficulties [29]. In moderate TBI, patient is lethargic or stuporous, and in severe injury, patient is comatose and unable to open his/her eyes or follow commands. The illustration of such TBI is shown in Figure 2.6 (adopted from [30]).

Neuromuscular impairments: Individuals with TBI commonly exhibit impaired motor function. Upper extremity (UE) and lower extremity (LE) paresis, impaired coordination, impaired postural control and abnormal tone may be present as life-long impairments. Abnormal, involuntary movements such as tremor and chorea form and dystonic movements are less common. Patients may also present with impaired somatosensory

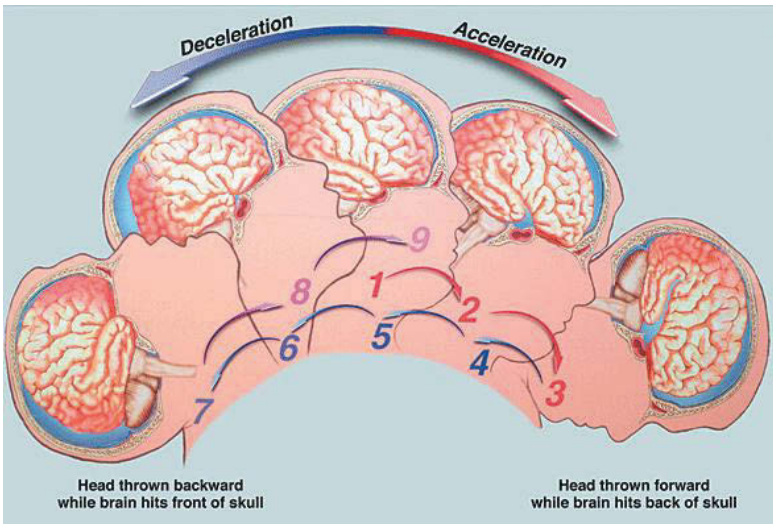


Figure 2-6: Example of Traumatic Brain Injury

function, depending on the location of the lesion [31-33].

Cognitive impairments: Cognition is the mental process of knowing and applying information. Owing to the complex nature of many cognitive processes it is difficult to localize the exact neuroanatomical structures responsible for many different cognitive functions. However, many cognitive functions are controlled in the frontal lobes. This makes people with TBI particularly susceptible to the cognitive impairments. Cognition includes many complex neural processes, including arousal, attention, concentration, memory, learning, and executive functions [34, 35]. Executive functions can be categorized into the following main areas: planning, cognitive flexibility, initiation and self-generation, response inhibition, and serial ordering and sequencing [36].

Neurobehavioral impairments: Patients can exhibit profound behavioral changes as they progress through recovery. These impairments can be closely linked to the cognitive impairments and are often more debilitating in the long run than physical disability. Common behavioral sequelae include low frustration tolerance, agitation, disinhibition, apathy, emotional lability, mental inflexibility, aggression, impulsivity, and irritability [36].

2.2.1.3. Spinal Cord Injury

Spinal cord is the extension from the brain stem and out to the body through peripheral nerves. The sensory stimuli are carried from peripheral nerves through the spinal cord to the brain to enable tactile perception and coordinated movements. Hence the injury or damage to the spinal cord can result in loss of communication between the brain and the parts of the body that are innervated at or below the lesion. The lesion may be complete in which no nerve fibers are functioning below the level of injury or incomplete in which one or more nerve fibers are secure. The cord need not be completely severed to result in a complete injury; the nerve cells may be destroyed as a result of pressure, bruising or loss of blood supply. The amount of functional loss depends on the level of injury: the higher the damage occurs, the more of the body that is affected. The example of SCI is illustrated in Figure 2.7 (adopted from [37]).

Motor and Sensory impairments: Following SCI there will be either complete (paralysis) or partial (paresis) loss of muscle function below the level of the lesion. Disruption of the ascending sensory fibers following SCI results in impaired or absent sensation below the level of the lesion. The clinical presentation of motor and sensory impairments depends on

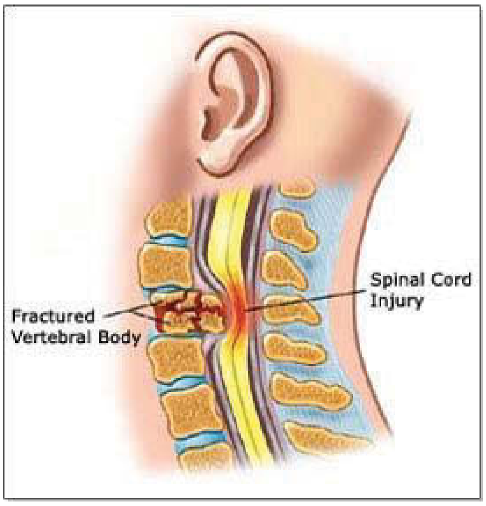


Figure 2-7: Example of Spinal Cord Injury (SCI)

the specific features of the lesion. These include the neurological level and the completeness of the lesion.

In any neurological disorders, as mentioned above, the most common effects that victims experience is the significant motor and cognitive disabilities which are the interest of this thesis. In the context of motor disabilities, a person's physical functioning, mobility, dexterity or stamina is limited and this leads to prohibit the performance of daily life activities. In the context of cognitive disabilities, a person may lose memory and/or speech which may greatly affect the victim's interaction in social activities. These effects will lead the victim to depression and this is common and occurs in most of the victims. It is characterized by persistent feelings of sadness accompanied by feelings of hopelessness, worthlessness, and/or helplessness. Depressed patients may also experience a loss of energy or persistent fatigue, an inability to concentrate, and decreased interest in daily life along with changes in weight and sleep patterns, generalized anxiety, and recurrent thoughts of death or suicide. However there is a way to recover from their impaired conditions although the recovery rate is much dependent on how severe the damages are. This is through "Rehabilitation" therapy which has an important role in reducing permanent disability, recovering from minor disability and leading to promote an individual's independence.

2.3. Rehabilitation

Rehabilitation is the process of training someone to recover or improve his/her lost functions as a result of injury or illness and it should start as soon as the medical condition of the victim is stabilized. In order to achieve successful rehabilitation, team work is expected in which physiotherapists, occupational therapists, speech therapists, nurses, neuropsychologists, rehabilitation physician, and social workers contribute. In general, physiotherapists and occupational therapists work together to achieve the independent daily activities where speech therapists will focus on the patient's production of motor function for speech, chewing and swallowing. Nurses and rehabilitation physicians work closely together to monitor and control patient's health such as hypertension, diabetes, urinary system and their diets. Neuropsychologists are responsible to achieve to regain their lost memory, concentration, willpower and motivations. Social workers also help patients to achieve a better quality of life and hence play one of the major roles in the rehabilitation program.

There are three major settings for rehabilitation namely the acute hospital, the specialized rehabilitation unit and the community. The procedure for the patient is as follow: when patient is admitted to the hospital, he/she should be sent to a specialized unit where they are checked with magnetic resonance imaging (MRI) or computed tomography (CT) scan and their treatment decided upon. Patient will then receive the rehabilitation assessment within 48 hours and be under observation for any complications. Once the patient is medically stable, he/she can undergo rehabilitation at specialized rehabilitation units until his/her impairment has improved. Although the patient is in rehabilitation unit, regular reassessment must be done. Patient can receive rehabilitation as inpatient, outpatient or home-base services. All of these services provide a higher quality program. After improvement in patient mobility or there is no further functional improvement, patient can be discharged from rehabilitation unit and transferred into community where a general practitioner and carer take on the vital role of taking care of patients [38].

Successful rehabilitation relies on intensive training and exercising, and repetitive practice of functional movement helps victims to develop skills for changing conditions that pose barriers in their lives [39]. Improvement is directly proportional to the effort put in by the patient into the training, and this effort is best evoked in traditional rehabilitation by the therapist [40]. In order to achieve such successful rehabilitation, one-to-one attention between patient and therapist are required and this is current practice in most of the rehabilitation settings. This lead to therapist fatigue as generally, the numbers of therapists are usually much lower than the number of patients. For instance, the registered physiotherapists in Australia are about 25,000 people according to 2012 report by Physiothrapy Board of Australia [5] and this is about 8:1 (patients: therapist) ratio. This implies one physiotherapist has to take care of an average of 8 patients at a time and hence this leads to a shortage of therapists in rehabilitation settings. In addition, this greatly impacts on the outcome of rehabilitation as well as the wellbeing of physiotherapists. Generally, rehabilitation is mainly focused on patients' progress in their recovery from impairments and therapist and caregivers' burden has been neglected. That is why in rehabilitation context, this becomes one of the major issues. Additionally, the high cost of rehabilitation is a burden for both victims' families as well as for the country. As a result, the duration of primary rehabilitation is getting shorter and shorter which leads to an increase in the prevalence of both moderate and severe disabilities in the population [41]. In order to overcome such limitations, technology based rehabilitation systems are introduced to lessen the fatigue of therapists and carers; these rehabilitation systems require minimum supervision during rehabilitation therapy.

Among the several areas of rehabilitation required for recovery from neurological disorders, in this thesis, upper limb motor rehabilitation and cognitive rehabilitation are the focus because these are the most important functions in order to improve the victim's quality of life. In addition, the proposed systems in this thesis will also lessen the caregiver burden and allow the patient to perform the daily life activities independently by improving the upper limb functions. Therefore, in this literature, rehabilitation systems that improve upper limb motor functions and cognitive functions along with the recent available technologies are reviewed in section 2.5. One of the main reasons for recovery by physical rehabilitation is due to the excitation of human neuroplasticity which will be explained in the following section.

2.4. Neuroplasticity

Neuroplasticity refers to changes in neural pathways and synapses due to changes in behavior, environment, neural processes, thinking and emotions. It is the mechanism by which the brain encodes experience and learns new behaviors. It is also the mechanism by which the damaged brain relearns the lost behavior in response to rehabilitation. Learning is an essential component of brain adaptation to brain damage even when there are no overt rehabilitation efforts. One of the most reliable behavioral consequences of brain damage is that individuals develop compensatory behavioral strategies to perform daily activities in the presence of lost functions [42]. These self-taught behaviors are potentially among the most significant behavioral changes of an individual's life. However, they can also be maladaptive and interfere with improvements in function that could be obtained using rehabilitative training. For instance, after unilateral brain damage, although reliance on the less-affected body side is associated with major neuroplastic changes in the unaffected hemisphere, this reliance may also limit the propensity of individuals to engage in behaviors that improve function of the impaired body side [43].

It has been observed by a remapping of the surrounding areas of the lesion [44]. To maximize the brain plasticity, several rehabilitation strategies have been proposed that rely on a putative promotion of activity within surviving motor networks. Those strategies include intensive rehabilitation [45], repetitive motor training [46], techniques directed towards specific deficits of the patients [47], mirror therapy [48], constraint-induced movement therapy [49], motor imagery [50], action observation [51], etc.

By understanding the basic principles of neural plasticity that govern learning in both intact and damaged brain, identification of the critical behavioral and neurobiological signals that drive recovery can begin. There are ten principles of experience-dependent plasticity which are proposed by [52] and detail of each principle is explained as follow:

Principle 1: Use it or lose it

This is an important principle in rehabilitation research for two reasons. The first reason is that failing to engage a brain system due to lack of use may lead to further degradation of function [53]. The second reason is that functional recovery may be supported in at least part of the lesion area by shifting novel function to residual brain areas. Therefore, by performing the rehabilitative training in a skilled reaching task may prevent such loss and functional reorganization is promoted [54].

Principle 2: Use it and improve it

Training that drives a specific brain function can lead to an enhancement of that function. Several studies have proven how plasticity can be induced within specific brain regions through extended training [55-57].

Principle 3: Specificity

Specific forms of neural plasticity and associated behavioral changes are dependent upon specific kinds of experience [58]. The implication for rehabilitation is that training in a specific modality may change a limited subset of the neural circuitry involved in the more general function and hence influence the capacity to acquire behaviors in non-trained modalities.

Principle 4: Repetition Matters

The role of repetition in stimulating plasticity and associated learning may be critical for rehabilitation. Simply engaging a neural circuit in task performance is not sufficient to excite the nature of plasticity. Therefore, repetition of a newly learned or relearned behavior may be required to induce lasting neural changes. It has been proven that some forms of plasticity require not only the acquisition of a skill but also the continued performance of that skill over time [59].

Principle 5: Intensity Matters

In addition to the repetition, the intensity of stimulation or training can also affect the induction of neural plasticity. The experiment on this principle was conducted and proven by [60, 61]. However, one potential negative side effect of training intensity after brain damage is that it is possible to overuse impaired extremities in a manner that worsens function. Therefore it is important for the therapist to observe the patient performance and set the proper intensity during the rehabilitation therapy.

Principle 6: Time Matters

The neural plasticity underlying learning can be best thought of as a process rather than as a single measurable event. Certain forms of plasticity appear to precede and even depend upon others. Thus, the nature of the plasticity observed and its behavioral relevance may depend on when one looks at the brain. The stability of the plastic change may also depend upon the time after training. Stimulation experiments have shown that enhanced synaptic responses are more susceptible to degradation during early phases of stimulation than later [62]. The time factor may be even more critical after brain damage given the dynamic changes in the neural environment that are occurring independent of any rehabilitation [60].

Principle 7: Salience Matters

Saliency is already an important consideration in the treatment of many neurological disorders, including aphasia and motor speech disorders. However, a better understanding of the neural processes underlying the modulation of recovery processes by saliency may be useful for optimizing treatment. Several experiments have demonstrated that there is a neural system that mediates saliency and that engaging this system is critical for driving experience-dependent plasticity [59-61].

Principle 8: Age Matters

It is clear that neuroplastic responses are altered in the aged brain [63]. Experience-dependent synaptic potentiation, synaptogenesis and corticalmap reorganization are all reduced with aging. In addition, cognitive decline may reflect the progressive failure of plasticity processes in compensating for age-related impairments. However, the aging brain is also clearly responsive to experience, even though the brain changes may be less profound and/or slower to occur than those observed in younger brains [64].

Principle 9: Transference

Transference refers to the ability of plasticity within one set of neural circuits to promote concurrent or subsequent plasticity. This phenomenon has been recently demonstrated in human motor cortex with skill learning and transcranial magnetic simulation (TMS). When TMS was applied to motor cortex synchronously during skill training, it enhanced skill acquisition [65].

Principle 10: Interference

Neural plasticity often has a favorable connotation in the context of recovery of function. However, plasticity can also serve to impede behavioral change. Interference refers to the ability of plasticity within a given neural circuitry to impede the induction of new, or expression of existing, plasticity within that same circuitry. This, in turn, can impair the learning. Although some types of noninvasive cortical stimulation applied during or shortly before skill training may enhance motor learning [65], other forms can be disruptive of learning. For example, transcranial direct current stimulation given after training reduced the training-dependent increases in cortical excitability [66]. Another reason to consider interference effects is that a therapy that benefits one skill may interfere with performance of another. Furthermore, as brain injury may change the neural response during learning, it may also change sensitivities to interference effects. For example, providing explicit instruction on how to perform a motor sequence task was found to improve implicit motor learning in healthy controls, whereas the same instructions interfered with learning in subjects with strokes [67].

By understanding the above mentioned basic principles to exhibit the neuroplascitiy nature, there is a higher chance to develop novel rehabilitation system to optimize functional recovery. However, such systems are very limited due to lack of one or more principles to incorporate in current available rehabilitation systems in the literature which will be reviewed in the following sections.

2.5. Robot based Rehabilitation Systems

Rehabilitation robot is the combination of industrial robotics and medical rehabilitation where collaboration of clinicians, therapists and engineers helps physical or cognitive impaired patients. Robotics has been envisioned as technology for restoration and functional compensation of people suffering from physical disability and disorders. There are two main application fields where robotic devices stand out: (1) support to perform the activities of daily life (ADLs) and to provide the physical training. Although the ultimate goal of the rehabilitation is the former one, the latter is the first step of rehabilitation therapy to achieve the ultimate goal. The use of the rehabilitation robot can be either in specialized therapeutic institutes or home-based conditions. Most of the proposed robotic rehabilitation systems in literature are mainly suitable for therapeutic institutes since they require supervised assistance from qualified personnel. The cost of such devices is also often prohibitive for personal use due to their complexity. Therefore, the demand for home-based therapy is expected to increase by most patients. However, Dijkers, et al. [68] pointed out that most of the therapists may stop using the rehabilitation devices if the set-up time takes more than 5 minutes. This is one of the major factors to consider when developing any rehabilitation system in which the new development should be intuitive, easy and fast to set-up with a reasonable and affordable price.

Among the various types of rehabilitation robotic devices available in the field, in this literature, the robotic devices are categorized based on their mechanical structures that are dependant on the movement. As mentioned in chapter one, there are two main basic types of rehabilitation robots, (1) end-effector or fixed-based type and (2) exoskeleton or wearable robot type. The difference between these two types is how the movement is transferred from the device to the patient’s upper limb. Selection of robot type is dependant on rehabilitation goal such as range of motions, kinematics criteria of the human limb, ambulatory and portability [69]. It was claimed that exoskeleton provides wider range of movement and it is portable compared to an end-effector robot. However, both of them require physical interaction with the device user. Physical interaction implies that there is a physical coupling between human and robot leading to the application of controlled forces between them. Thus, the action of both human and robot must be able to be coordinated and adapted reciprocally to avoid severe injuries. Therefore the designing of such device is one of the most exciting and challenging aspects with several constraints and requirements especially in the development of an exoskeleton as a human being is an integral part of the design.

2.5.1. End-Effector Robots

The end-effector based rehabilitation robots are usually connected to the patient upper limb with single point. Since early 1960, clinical community has been using continuous passive motion (CPM) machines, which had a simple motor-driven linkage, and were used to rehabilitate the joints following surgery [70]. It helped to regain the range of motion, reduce stiffness and the need of medication and reduce the length of stay in hospital [70, 71]. However, these machines were not able to reprogram, presence of design issues in joints with fixed axes of rotation and required lengthy setup time. Therefore, more and more effective rehabilitation devices (robots) and control techniques have been developing until now so as to accommodate the patients and therapists requirements. CPM robot was developed by Khalili and Zomlefer [72] for therapeutic applications. However, their developed robot was not fulfilled with patients and therapists requirements in terms of design and performance. The first in-depth study on the acceptance of robot technology in occupational therapy for both patients and therapists was carried out by [68]. His development provided successful repetitive reaching movements. However, the development was down by boring exercise, was expensive and lacking in monitoring of patient cooperation. Thus, the implementation of Rao et al. [73] used a 6-DOF Puma-260 robot to train the patient upper limb via end-effector with low cost motivated real-time visual feedback exercise. The system was controlled by two different modes: passive and active. In passive mode, robot controlled the patient’s arm via specified trajectory. In active mode, patient own movement guided the robot via predefined path according to the graphical interface similar to a tunnel. In his development, the robot end-effector was able to be traced and monitored with real-time visualization by the user. This visualization offered immediate feedback to the users to react and correct their limb motions. However, it was limited to a single plane and did not provide full entertainment as a three-dimensional game-like therapy for long term training. The first two unmodified industrial robots working simultaneously to practice passive physiotherapy of spastic hemiparetic patients was developed by [74] called REHAROB. The rehabilitation purpose of REHAPROB was to increase the range of motion, maintain proprioception and reduce muscle hypertonia. However, the system was not safe enough to employ as a therapeutic system after clinical trials had been done. Another serial manipulator, MIT-MANUS [75, 76], which is an impedance controlled five bar linkage planar robot, assisted shoulder and elbow therapy. After the successful clinical trial with this manipulator, it was extended from planar robotic therapy to spatial arm movements against gravity [13]. The therapeutic goal of this development was targeted for functional reaching movements. To extend the treatment envelope beyond the shoulder and elbow, additional wrist module was invented [3, 77] to complete a whole-arm rehabilitation system. However, the development was characterized by high back-driveability with high cost. Reinkensmeyer et al., [78] had developed a low cost rehabilitation robot to replace the high cost manipulator. It was a simple mechanical structure with no back-driveability. Inspired by Reinkensmeyer et al., development, a simple mechanical structure with low cost robot system, MEMOS [79] was developed for upper limb rehabilitation. It was a planar robot in a Cartesian configuration with a rectangular shape work place for patient movement.

Other than end-effector based robotic rehabilitation therapy alone, integrating with haptic feedback had shown improvement in the efficacy for cognitive training [80] and dynamic task [81, 82]. Several haptic displays [83, 84] were developed as an effective interaction aids for providing the sense of force or moment feedback to the user. Many haptic devices have been built and commercialized [85-88] with different features and have been used for upper limb rehabilitation training. Work in the context of haptic feedback in the rehabilitation of the upper limb was carried out by R. Loureiro [89, 90]. A haptic device named GENTLE/s which is based on 3-DOF HapticMaster [91] was developed. It was a low cost modular home based system with haptic and virtual reality system for upper-limb stroke rehabilitation. Alternative haptic-robotic platform was designed by Paul Lam et al. [92]. This development was inspired by Assisted Rehabilitation and Measurement (ARM) Guide [93]. The aim of ARM Guide was to provide an improved diagnostic tool for assessing arm movement tone, spasticity and coordination after brain injury. However, the system was bulky and heavy. The control system of ARM Guide was not user friendly as well. Thus, Paul Lam had designed the system, a lighter and more compact version with more intuitive and simpler hardware design. The control system for the new system was generated to make decisions with respect to the type of exercise automatically based on real-time feedback from the system and user.

In the frame work of bimanual training for upper limb, Johnson et al. [94, 95] had developed SEAT (Simulation Environment for Arm Therapy) which was one-degree-of-freedom robotic device for constraint-induced therapy to promote the bilateral movement coordination. The system can be utilized in three modes: passive, active and normal mode. During passive mode, non paretic arm was guided by the servomechanism to compensate for the weight of the paretic arm. The active mode was used after patient had shown the improvement of paretic arm voluntary control. In this mode, only paretic arm was controlling the car steering wheel while non paretic arm was relaxing. The normal mode was used to access distribution of force and limb's co-ordination. Same concept was used in MIME [96, 97], Mirror-image motion enabler, to produce the repeatable movement patterns in the paretic arm. MIME was able to perform either in pre-programmed position and orientation trajectories or slave configuration where it mirrored the motions of the non-paretic arm. The system enabled the subject to practice bimanual shoulder and elbow movements in the horizontal movement. However, MIME system was hampered by expensive cost with mechanism complexity.

A precursor version, reported by Lum et al. [98] was a robotic assist device for the bimanual practice of wrist flexion and extension. The robotic aid could substitute completely for one hand in a bimanual task but clinical data were not reported for this development. Arm Trainer Robot [99] enabled bilateral passive and active training for elbow and hand movements. This development was suitable for severely affected stroke survivors but there were no clinical data to verify the effectiveness of the developed system. The improved design and system configuration of bimanual robot compared to Arm Trainer Robot was developed by [100]. This system was targeted to decrease muscles spasticity, increase power and motor control and relieve pain in the arm of chronic hemiparetic patients. The additional feature that compared to Arm Trainer Robot was that the patient was able to realize the force feedback for real-time dynamic sensation of the paretic hand by healthy hand. Another bilateral force-induced isokinetic arm movement trainer (BFIAMT) was invented by Jyh-Jong Chang et al. [101] to improve arm movement. There are four different treatment modes which are applicable in this system namely bilateral passive, bilateral reciprocal, bilateral active-passive and bilateral symmetric arm movement. Patient was asked to perform bilateral symmetric push for shoulder flexion and elbow extension and bilateral symmetric pull for shoulder extension and elbow flexion with constant velocity. Load cells will detect pull and push forces applied by patient. Although the outcome of the training with BFIAMT shows improvement in upper limb motor function, the system did not monitor for trunk muscle activities and thus trunk movement compensation during maximal isometric push and pull tests could be present. Alternative self-controlled robot was developed by Chunguang Li et al. [102]. This intervention consists of two identical motors, master and slave, which directly connect with wire. The methodology of this system is realized by generating of electrical energy from master motor by healthy limb where slave motor receives as power to drive mirror movements of impaired limb. Master motor worked in generating state whereas slave motor worked in electromotive state. Both motors were constructed as close-loop circuit and energy recycling method had been attempted.

2.5.2. Exoskeletons or Wearable Robots

The exoskeleton robots are group of wearable robots with very remarkable applications in rehabilitation field. The main aspect of the exoskeleton kinematic compliance is one-to-one correspondence between human anatomical joint and robot joint. The interaction between the human limb and exoskeleton can be attained via external force or internal force system. In the context of external force system, the force is grounded and mechanical structure acts as a load-carrying device. Thus, only a minimum amount of force is acting on the subject. In contrast to an external force system, in an internal force system, the force and power is transmitted by means of exoskeleton between segments of human limb. Furthermore, the force is not grounded and it is applied only between human limb and exoskeleton.

2.5.2.1. External Force Exoskeleton System

The first development of the exoskeletons began in the early 1960s. Several external force exoskeleton systems [21, 103-105] were developed, but all those developments were lacking in one or more of the following features: low-inertia links, high stiffness transmissions, open mHMIs, low-backlash gearing, backdrivable transmissions or physiological range of motions. The first active implementation of functional upper-limb orthosis was developed by [106]. It was an external force exoskeleton system which provided a sense of floatation. It was made up of two links and 4-DOF and was mounted on a wheelchair. It operated by gravity-balancing the entire arm for all positions in 3-D motions, therefore required minimal effort to move the arm.

The 5DOFs upper limb rehabilitation robot system has been developed by Qingling Li et al [94]. 5 DOF have been defined at shoulder joint flexion-extension and abduction-adduction, elbow joint flexion-extension, wrist joint flexion-extension and pronation-supination. The idea of this system is to train the impaired limb with the aid of robot by making use of healthy limb's sEMG signals. The rehabilitation robot was made up of duralumin with a two-side structure which caters for tough and rigid design. The sEMG data that was obtained from mid-deltoid, front-deltoid, biceps brachii and brachioradialis were classified into six upper limb motions to drive rehabilitation robot to perform the same action with moderate speed. However, there was no report of performance and effectiveness of the system. In the development of ARMinII rehabilitation robot [69], a semi-exoskeleton structure was employed. It used 7 DoFs for whole arm and hand motion. The system used mechanical coupling concept between shoulder elevation actuation and elevation axis. Although the implemented concept provided safety even in control failure or power failure, this design reduced the range of motion in arm elevation. The design of the 3DoFs robotic exoskeleton, MEDARM [107] for rehabilitation is made up of cable-driven actuation unlike other development. In this design, the shoulder joint motion is realized by a curved track system which can be described as a 4-bar linkage with backdriveable facility, light weight and low friction. The major advantage of this system is the robot is placed beneath of the user arm which will reduce vertical compliance as the weight of the arm will be directly supported by the carriage near the elbow joint. To attain full motion capability, four cables are driven by electric motors.

The development of 6DOFs exoskeleton robot which was also known as SUEFUL-6 robot [108] for upper limb motion was done by R. A. R. C. Gopura et al. It was made up of 6 different types of harmonic drive which were used for shoulder vertical and horizontal flexion-extension motion, elbow flexion-extension motion, forearm pronation-supination, wrist flexion-extension and wrist radial-ulnar, pulleys, gears, potentiometers, sliders and other mechanism for moving and rotating parts. The axes offset and centre of rotation for movement are key points to build up the exoskeleton robot. sEMG driven 3DOFs exoskeleton for upper-limb motion assist was done by Kazuo Kiguchi et al [109]. The development was aimed for shoulder vertical flexion-extension motion, horizontal flexion-extension motion and elbow flexion-extension motion. Like other developments, the robot is made up of motors, pulleys, potentiometers and other mechanisms for moving centre of rotation. Making use of force sensor-based controller (FBC) and EMG-based controller (EBC) coupled to obstacle avoidance controller (OAC), a fully automatic power-assist controller was built up. When EMG level of user is high, EBC was use to control the system whereas when the EMG level of user is low, FBC would used to control the system. When muscles activity is in intermediate level, both EBC and FBC would be used simultaneously. OAC is to avoid accidental collision between user's upper limb and robot frame. The instantaneous force vectors which were derived from output of EBC at robot end-effector was to achieve user's natural and smooth hand trajectory for rehabilitation.

IntelliArm 8+2 DOF robot was developed by Yupeng Ren et al. [110] to rehabilitate the upper limb for stroke patients navigated with virtual reality. This is to diagnose the biomechanical changes and abnormal couplings at the shoulder, elbow, wrist and finger joints of the impaired arm. The system included four active DOFs and two passive DOFs at shoulder, 4-DOFs for elbow and one active DOF for hand opening-closing motion which were adapted in this system to imitate the real upper limb. Four-bar linkage with single motor was designed based on available space, weight and moment of inertia of the robot. Sliders, multi-motors, cables and pulleys, force sensors and torque sensors were utilized to develop the robot. In this robotic therapy strategy, four types of control were used namely intelligent stretch control, back-driven control, assistive control and resistive control. The error vector based on the difference between desired position and current arm position was used to decide either to assist or resist control to employ during training. According to the experiment result, IntelliArm provides accurate and quantitative diagnosis but the complete system is very bulky and it is a stationary system.

An articulated rehabilitation robot has been developed for upper limb physiotherapy and training [111]. This robot has 9 DoFs. The system is different from other exoskeletons in terms of motion principle. It employed parallel-motion principle instead of solving inverse kinematic solutions which is normally employed by most of the robots. The idea behind this is to find the position trajectories of the essential joint pivots of the robot given the knowledge of those of various joints of the human arm. The shoulder mechanism design [112] was designed for stroke rehabilitation. It has 6 DoFs, 3 for shoulder girdle movement while the other 3 DoFs provide conventional ball and socket joint movement thus it allows the alignment of CGH (center of glenohumeral joint) position and orientation of humerus. The design followed RPRPRR (Revolute-Prismatic-Revolute-Prismatic-Revolute-Revolute) joint sequence to overcome the problem of being insufficient for rehabilitation tasks due to collision of components with each other which is normally faced by other robots.

Other than the use of motor driven exoskeleton as reported in above literatures, rotational hydroelastic actuator was used to drive the powered exoskeleton in Arno H. A. Stienen et al. proposed system, Limpact [113, 114]. Series elastic actuation (SEA) and rotational hydraulic actuators were directly mounted on exoskeleton joints. The system was driven by symmetric torsion spring, high-precision quadrature encoders and potentiometer and strain gauges. There are three rings that were attached to rHEA. Making use of these rings, actuator torque will eventually be achieved due to angular difference during movements. Both compliant impedance control and stiff admittance control were used in the Limpact system. Although the system was suitable for rehabilitation therapy, the requirement of pump, noise issues and hydraulic leakage became a problem in clinical settings.

As far as pneumatic based exoskeleton is concern, bi-articular muscle type HBSA (Hydraulic Bilateral Servo Actuator) [115] is presented. This design mimics the antagonistic pairs of actuators in human joints. It has proven to be able to reduce the number of actuators by having bi-articular type actuators to operate two joints with light weight and high output. The control architecture of the system is that the motion control system of the arm is determined by pressure sensors that detect the patient’s movements. The pressure analog signal is converted to digital data and sent to a microcomputer to drive the motor. The control of the trajectory used linear interpolation in three dimensions using DDA (Digital Differential Analyzer) method. Pneumatic driven upper limb exoskeleton, Salford Rehabilitation Exoskeleton (SRE), was developed by S. Kousidou et al. [116] to provide upper limb rehabilitation. It had 7-DOF and controlled shoulder flexion-extension, shoulder abduction-adduction, shoulder medial-lateral rotation, elbow flexion-extension, forearm pronation-supination, wrist flexion-extension and wrist abduction-adduction movement. With the aid of position valves and torque valves, switching sequences of exoskeleton pneumatic valves will be followed by regulating the amount of required air which will be pumped into the pneumatic muscle actuators which will achieve exoskeleton motion. However, current pneumatic actuated exoskeleton rehabilitation system could perform only very limited tasks and future research in this area is required.

2.5.2.2. Internal Force Exoskeleton System

In the framework of an internal force exoskeleton system, RUPERT (Robotic Upper Extremity Repetitive Therapy device) has been implemented by [109]. In this design pneumatic muscle (PM) has used as a robot actuator. It used four pneumatic muscles to provide 5 DoFs: 2 at shoulder, 2 at elbow and 1 at wrist. To provide both extension and contraction of the pneumatic muscle, springs have been incorporated into pneumatic muscle. The control method of the robot is using pressure data and joint data which will be sent to SimMechnics to determine the joint velocities, accelerations and inertia. Making used of inverse dynamics calculations, required torque can be estimated to drive the RUPERT arm. Once dynamic torque is estimated, torque supplied by PMs can be determined. Therefore robot arm can estimate the voluntary muscle activity at each joint by subtracting estimated dynamic torque from torque supplied by PM. The significant design specification of RUPERT was non-gravity compensation in 3D workspace. However, this system had limited workspace and catered for simple movements of daily life activities. Alternative design of internal force exoskeleton system was 5 DoFs arm exoskeleton for shoulder rehabilitation system which was reported by [117]. This system allows for scapula motion and first order approximation of shoulder translation by means of single rotary joint. The intention was to place singularity at an azimuth and elevation so that can avoid interference with rehabilitation tasks. Shoulder elevation and depression movements are accomplished by single rotary joint perpendicular to the back.

Another upper limb exoskeleton with internal force system has been developed by [118]. The aim of this design is that no residual forces can be created in the human joints if misalignments of the mechanism to the human joints exist. It only required minimum time for dressing on and off. The mechanism that interacts with shoulder girdle is comprised of 6 DoFs in order to avoid singular positions and collide with human body during articulation such as shoulder circumduction. As for elbow interaction, 3 DoFs mechanism has been used to eliminate the misalignment problem for elbow flexion-extension. Since misalignment of forearm pro-supination axis is not critical, 1 DoF mechanism is designed for forearm pro-supination motion. For the interaction of wrist to be smooth with eccentric motion dedicated by the ellipsoid radio-carpal joint, 6 DoFs mechanism is required.

The 4 axis ABLE exoskeleton for upper limb has been developed by [119]. The unique design of this robot is that it allows hybrid force-position control without requiring any force sensors. Like other exoskeletons it is back-drivable, has a high efficiency with low inertia actuators. Moreover, the system permits high performance of mechanical transmissions via screw and cable patented arrangement. The use of cable transmission concept provided the advantages in shock absorption and smoothness. The design of the shoulder joint is a spherical articulation made up of three orthogonal pivots which have a common intersection which approximately coincides with the centre of the human shoulder. To eliminate singularity at shoulder joint, the second joint which takes care of internal and external rotation of shoulder is designed with a circular guide. Another design of internal force exoskeleton system for elbow and forearm movements has been reported by Rahman [97]. This is a 2 DoFs ExoRob that requires to be worn on the lateral side of the forearm and provides naturalistic range of movements: elbow flexion-extension and forearm pronation-supination motions. The new gear mechanism design where power is transmitted from anti-backlash gear to meshing ring gear which is rigidly attached to the forearm cup is introduced. The control algorithm for this developed system is based on non-linear sliding mode control technique. This development is currently working towards 7 DoFs motion assisted robotic exoskeleton.

The 3 DoFs wearable handling support system for a paralysed patient is developed by [69]. In this system, three rotation angles of patient's head namely pitch, yaw and roll are used to control the 3 DoFs support system which are angle of elbow joint, angle of wrist joint and hand close/open. Patients were required to wear a cap with accelerometer on it and power assistive hand and arm support system during training. The support system was controlled by the detecting of three motions of patient's head including pitch, roll and yaw motions. Then there were six DC motors to drive finger mechanism and it can be separated into two drive parts: three motors for index finger and three motors for the three coupled fingers. They were connected via universal joint that allowed fingers to adduct and abduct and permits a palm to deform for finger opposition. The thumb mechanism was driven by two links, two wires and two actuators. The test results reveal that the system had enough working angles of each joints and assistive force to carry out specified exercise. Wrist exoskeleton has been developed for neurorehabilitaion [120]. The mechanism is based on two cables passing through two guides placed laterally on the chain-like mechanism. During flexion-extension motion, the displacements of the cables are symmetric and during radial-ulnar deviation, it will become asymmetric. Therefore, it can determine the flexion-extension and radial-ulnar deviation angles. However the developed system is affected by errors due to external crosstalk on which future work needs to be done.

However, most of the above literatures from exoskeleton or wearable robot met with the problems related to the alignment or singularity of robot and human joints: shoulder, elbow and wrist either in external or internal force system. Thus, researchers have started to investigate and invent the alignment free exoskeleton and literatures are reported in below section.

2.5.2.3. Alignment-Free Exoskeletons

As far as singularity problem in upper limb exoskeleton design is concerned, proper control method to avoid misalignment at elbow joint has been studied by [118]. This is a 4 DoFs (two rotational and two translatinal) passive self-aligning mechanism, NEUROExos, which allows the actuated joint axis to be always aligned with the instantaneous human joint rotation axis. The double-shell link structure is employed in this development to reduce the pressure on the user's skin compared to other exoskeleton designs. It is powered by a variable impedance antagonistic actuator which provides the exoskeleton with software controllable passive compliance [121]. The 7DOFs cable-actuated dexterous exoskeleton for neurorehabilitation (CADEN)-7 was created by Joel C. Perry et al [90]. The unique design concept of this exoskeleton is proximal placement of motors and distal placement of cable-pulley reductions which will provide low inertia, high stiffness link with zero backlash. Seven single-axis revolute joints were use in this intervention. To take care of alignment problem, singularity placement was carefully considered at shoulder joint. To limit the robot joints range of motion, motion capture system (Vicon, 10 cameras) were used to capture joints positions of 19 activities of daily living in this intervention. Another elbow exoskeleton design with correct dimensioning to avoid singularity problem is currently being developed by [14]. In his study, elbow topology, singularities, torques transmitted to exoskeleton joints, and influence of soft tissues and cuffs compliances have been investigated. An alignment free 2 DoFs rehabilitation robot for shoulder complex called shouldeRO has been developed by [122]. This robot is specially designed to minimize the requirement of tedious and accurate alignment of robot and patient joints. It was composed of poly-articulated structure whose actuation is deported and transmission is realized by Bowden cables. The constant tension in the cables is completed by mechanical inverter. The proximal end of the robot is rigidly fixed using rucksack structure while distal end is fixed to the patient through splint. Based on the test result, due to the reaction forces at the shoulder, subject feels uncomfortable while training and this has to be addressed in future work.

Alternative compliant exoskeleton device for elbow joint rehabilitation has been implemented by [123, 124]. In his design, one passive rotational joint and one passive translational joint are added based on one active rotational joint to solve the centre disparity of elbow joint during flexion and extension. Kinematic function of the new mechanism has been proposed and used to calculate the position of elbow joint axis. Two force sensors were used to detect the angle and displacement of two passive joints. The experiment has been done and results have revealed that this design can solve centre disparity at elbow joint axis. Another development has been reported to compensate for the migration of Instantaneous Centre of Rotation (ICR) at joint and avoid mismatches during users' movements [125]. It is a dynamic servo adaptation based on three active DoFs mechanism design which can accommodate different anthropometric arm or leg measurements. The proposed design can be applied to any joints that produce movements in the sagittal plane. His developed algorithm permits the system to adapt itself to any ICR variation, maintain the initial adjustment of the orthosis and avoid any offset between device and user's limb. However, his development cannot cater for portable, lightweight and autonomous exoskeleton design. The exoskeleton robot for shoulder joint motion assist has been developed [126]. The unique feature of this exoskeleton is the centre of rotation (CR) of the shoulder joint of the exoskeleton uses a moving mechanism. The mechanism is made up of links and a slider. This design permits the CR of robot shoulder joint to move behind in accordance with shoulder vertical flexion angle during vertical flexion movement, and move inward in accordance with shoulder horizontal extension angle in the case of horizontal extension movement.

The 5 DoFs MAHI Exo II [84] exoskeleton has been developed for elbow, forearm and wrist rehabilitation. The mechanism design consists of a revolute joint at elbow, a revolute joint for forearm and 3-RPS (Revolute-Prismatic-Spherical) serial-in-parallel wrist. In his design, wrist mechanism uses Hephaist-Seiko SRJ series high precision spherical joints with inclined surface design on the wrist ring to improve range of motion. This will solve the minor misalignments of the wrist rotation axes with the device. As for forearm mechanical design, cable driven mechanism is employed for high torque output with simple mechanism and low cost. As for elbow design, two high torque DC motors with cable drives mechanism is assembled in such a way that enable it to change the transmission from one side to the other side easily and quickly for both left and right rehabilitation. This is achieved by coupling or decoupling of the capstans with the driving motor shaft via removable taper pins. To maintain better posture during rehabilitation, tilting mechanism as a passive DoF is implemented in the developed system. Some other developments of alignment-free robot were reported as in previous section internal force exoskeleton system [71, 117, 119].

Nevertheless, all of the rehabilitation robots were very bulky, heavy and especially the external force exoskeleton system requires a stationary platform to attach the robot arm which will make the user feel very uncomfortable. Although high safety paradigm is set for robotic rehabilitation system, it is still a high risk for the patient. In addition, most of the robotic approaches only focus on the movement training without any motivation. Therefore the robotic approach may lighten the burden of physiotherapist but will be still similar to the traditional rehabilitation therapy in which patient becomes bored after some period of time due to repetitive training manner. In order to overcome the limitations related to the robotic approach, virtual reality (VR) or augmented reality (AR) technologies are increasingly attracting much attention in the rehabilitation field due to its safer training environment with many motivational ways through gaming system as well as low cost training settings.

2.6. Game based Rehabilitation Systems

The Rehabilitation Gaming System (RGS) is based on VR or AR and is targeted for the induction and enhancement of functional recovery after lesions to the nervous system using non-invasive multi-modal stimulation.

2.6.1. Virtual Reality System

Virtual reality (VR) is a set of computer technologies that provides an interactive interface to a computer generated environment. In this environment, the individual can see, hear and navigate in a dynamically changing scenario in which he or she participates as an active user by modifying the environment according to his or her actions. VR has also been deployed in different rehabilitation contexts with a number of distinguishing features. First, they can be used as training tools to promote intensive training directed towards specific deficits. Second, training can be defined within scenarios that allow the patients to engage in task-oriented activities. Third, it is a real-time high-resolution monitoring tool, allowing for the quantitative assessment of relevant properties of deficits, performance and recovery. Fourth, the versatility of VR technologies can play an important role in engaging motivational factors, a key factor in recovery [127]. Fifth, VR based rehabilitation systems easily transfer from clinic-based training to at-home applications for telerehabilitation, creating a continuum of diagnostic and training possibilities [35, 128]. Attention and motivation are two major factors in neuroplasticity rehabilitation. Research studies have confirmed that virtual reality based rehabilitation therapy provides such sustained attention, motivation and self-confidence [29, 129]. It provides rich controllable multi-modal simulation and the possibility for individualization. It is a computer based interactive, multisensory simulation environment that occurs in real time. VR can be two types, immersive and non-immersive. Under fully immersive VR rehabilitation systems, large screen projection (LSP) [130], head-mounted display (HMD) [131]or cave (BNAVE) [132]were used for rehabilitation therapy. In a non-immersive VR system, interface devices such as computer mouse, cyberglove/cybergrasp [133, 134], joystick [135]or force sensor were utilized for rehabilitation training.

Some researchers have developed the combination of biofeedback and VR to rehabilitate the upper limb. The researchers from [126] have developed EMG biofeedback based VR system to train the hand rotation and grasping. The inputs for the system will be EMG system and magnetic motion tracking system while the output will be PC monitor where VR engine, software and database are installed. VR engine is used to create the VR environment for the system where the data base in which is also stored the results of each patient is to provide respective feedback and display via I/O driver. Polhemus Fastrak 3-SPACE magnetic motion tracking system which provides 6DOFs measurements is to detect the position and orientation of the patient's hand so as to achieve real time motion in VR environment. MP100, BIOPAC system Inc. EMG biofeedback system will detect patient muscle activity and it will convert analogue data to digital data via DATA TRALASION, DT9816. Desktop monitor will provide the VR visual output. The balloon shooting has been developed in this system as a rehabilitation task to improve patient hand rotating and grasping rehabilitation. VR system is developed by XNA game studio and programmed in C#. In VR environment rotation of the hand will be detected from motion tracker while grasping will be detected from processed EMG signal. The orientation of the hand data will be sent to VR engine via tracker next to PC and receiver at the patient's hand. In balloon shooting task, hand rotation will be represented as control of missile launcher head pointing direction. The raw EMG data which is collected from EMG system will be rectified, filtered by fourth order Butterworth band-pass filter to be represented as firing the missile in VR balloon shooting task. Both visual and audio feedback will be provided throughout the task. Adjusting of training task level will be available in this system based on patient's motor performance. Future work will focus on deep impression stereoscopic view with head-mounted display and will develop various rehabilitation tasks.

Hands-Up game was designed by Odle et al. [136]. It was implemented for children with orthopaedic disabilities. The system aims to improve finger control, grasp strength and bilateral hand coordination. The system was developed under Matlab's Simrobot toolbox and electromagnetic position/rotation sensor was used to track the current position of the hand in 3D space. It uses markers: paper cup, shirtsleeve and plastic spoon, to define the games based on therapeutic goals. The colour detection method was used to locate the position for one of the three coloured markers in gaming environment via webcam to start the game. The avatar hand which representing patient's real hand will appear in display screen to interact with virtual object in VR game environment. Participants demonstrated improvements in reaching movements ability and completing the functional tasks during usability study.

Another VR based video game was developed for rehabilitation of the pronation and supination movements of children with CP [137]. The game was implemented with LabVIEW and MATLAB for analysing the results. The game is a formula one racecar on a racetrack. The objective of the game is to keep the car inside the racetrack's limits. The pronation and supination movements of the user's forearm control the car's horizontal position on the screen.

2.6.2. Augmented Reality System

Although VR based rehabilitation systems have strong advantages over traditional methods or using any mechanical assist device, the system does not allow the patients to observe and communicate with the real world. In other words, virtual reality based rehabilitation system can be completely immersed in the synthetic environment or required head mount display for some of the developments. Moreover, the attachment of bulky tracking device, cyber glove, data glove or any haptic device to user arm, especially in non-immersive environment, becomes inconvenient for disabled patients due to its size and weight. Thus, alternative technique called augmetned reality (AR) has been studied and developed as a rehabilitation tool by researchers recently. AR allows patients to communicate with real world and it supplements reality rather than replaces it. Azuma in [138] defined AR as " a variation of Virtual Environments (VE) and let the virtual and real objects coexist in the same space". This new technique does not require any extra devices to track the subject's arm position except light weight marker which is appropriate for physical rehabilitation. Augmented reality is the combination of real world and virtual world that enhances the user perception of reality.

According to Ronald Azuma et al.[139], AR system must have the following properties: combines real and virtual objects in real environment, runs interactively and in real time, and registers (aligns) real and virtual objects with each other. There are two basic types of display for AR system namely see-through AR display and monitor based AR display [140]. In the context of see-through display, user can see the display medium directly to the real world surrounding whereby perceiving both the maximal possible extent of presence and the ultimate degree of image replacement. In monitor based display, user can view the computer generated virtual world which is overlaid on top of real environment via captured real-time video images. Most of the recent developments for AR based rehabilitation system were based on monitor based display due to its safer training environment. Due to its safe interaction environment, especially for children who are more sensitive to total immersive virtual world than adults, AR has been widely used in rehabilitation therapy. Moreover, AR provides a more real feeling than VR as it combines the real world and the virtual world seamlessly.

Such AR based rehabilitation was invented by J. W. Burke et al. [141, 142] with several games for upper-limb stroke patients. This development let them use real objects which will interact with virtual environment. His development is implemented in Microsoft XNA programming environment with C# and .NET Framework, and uses DirectShow library for image processing from webcam. The colour tracking method of the marker in this development is done in 2D space with segmentation algorithm. In this algorithm, RGB colour model was chosen as a colour space due to it being more effective than HIS and CMYK according to previous research. A short calibration was conducted to track the defined colour. The technique to track the colour is defining mean colour vector which is calculated from the pixels within the calibration square. During the game running, pixel's colour in each frame was being checked within a cuboid centred on the mean vector with three equations. If the component of each pixel satisfies all the equations, it is segmented as being same colour as marker and will be represented as a marker. Several augmented reality games such as Rabbit Chase, Arrow Attack and Brick'a'Break, were designed in this development by making use of marker-based augmented reality. This rehabilitation aim of these games is to regain the patient's motor functions such as grasp, reach, lift and release and cognitive skills.

Another AR based upper limb rehabilitation exercise, AR-REHAB, was developed by Atif Alamri et al. [143] for post stroke patient rehabilitation. The system was based on augmented reality games to improve patient's arm reaching and hand grasping ability. The system developed the framework which consists of patient subsystem and therapist subsystem. Under the patient subsystem, six components: sign-on, AR rendering, patient interface, tracking interface, session recorder and exercise adaptor are developed. Patient is required to sign into the system so that the appropriate AR exercise will be rendered. The rendering will take place by patient interface and tracking interface. The movements will be recorded with session recorder that applies some filters to reduce the amount of data and store it in the database. The exercise adapter is used to manipulate by therapist interface to modify the patient profile or treatment plan. Under therapist system, three components: session evaluator, decision support engine and therapist interface are available. The session evaluator will extract the useful data and store it as patient's performance data. Patient's performance will then be checked by decision support engine and this sends the recommendation messages via therapist interface as performance result. The system was developed in C++. The AR rendering was done with ARToolKit API, CHAI 3D API, Open Dynamics Engine (ODE) and VirtualHand SDK. ARToolKit API was used to detect the suspected marker pattern which is a preidentified image label via webcam. CHAI 3D API was used to overlay the scene graph of the virtual environment onto the real scene based on computed marker pose. Collision detection between objects and computer responses was computed with ODE. Although VirtualHand SDK provides the pose of hand, the system only used ARToolkit API to track the hand pose.

The development aimed to treat patient without the need of direct supervision of an occupational therapist. There are four games which were developed as AR-REHAB exercises namely shelf, cup, cannonball, air-hockey and block. The system has already conducted the usability test and provided positive results. However, occlusion problem and deterioration of depth perception need to be improved. Moreover a vision-based finger measurement system is needed to measure the position of the object in real time.

Alternative AR rehabilitation exercises were developed by [144]. AR drink, AR dance and AR fold were developed to improve the coordination of stroke patients. The system has been developed to train the patients' upper limb for daily life activities such as drinking, dancing and folding via virtual objects. The system is still under development towards orthopaedic conditions and management of chronic illness by controlling devices using body gesture and to provide validation results.

Dunne et al. [145] describe the rehabilitation system with multitouch display for age seven to eleven children with CP. The system is made up of multitouch display, tangible object input and wearable accelerometer. One of the main features of this system is the ability to track the trunk position of patient and discourage the compensatory movement which promotes the maximum effectiveness for this therapy. The tracking is made by accelerometer via Bluetooth connection and the processed data is sent to the display screen as a feedback. The system aims for stretching and coordination of upper-extremity using one or both hands and is integrated with three rehabilitation games: Find the bone, Spelling and Catch the butterflies to serve as a complete system. However, the measurement of range of motion progress is not so effective due to compensatory feedback alone.

To prove the advantages of AR technique in child rehabilitation, the preliminary study of augmented reality based rehabilitation system for cognitive disabled children has been conducted [146]. In this system, the non-immersive recreational and educational augmented reality application ARVe (Augmented Reality applied to Vegetal field) has developed. The ARVe helps cognitive disabled children in decision making by matching task of plant entities. Sensory cues such as visual, auditory and olfactory feedback were displayed in order to provide the correct decision by children. The system consists of laptop, webcam, video projector and Magic-Book like user interface where markers are attached on it. The main framework of this application is developed in C++ and Open GL library while augmented reality environment is built up using ARTag software library. The experimental study was conducted to investigate the children performance in using AR technique as well as to examine specific attitudes of cognitive disabled children. The study proved that the use of AR technique by disabled children promoted positive emotions and high motivation.

Other than proof of motivation with AR technique, various AR based rehabilitation systems help to improve the disabled children. The researchers from [147] have developed two augmented environments (AEs) for paediatric rehabilitation to improve motor control via music playing AE and topographical orientation training to relearn the community mobility skills through decision making AE. The system used USB webcam to capture the child movements and received images were processed by custom software. Movement tracking, detection and filtering are deployed when necessary by particular application. When collision of virtual objects is detected, software will send out visual and acoustic feedback to the user. In the framework of music playing AE, children with cerebral palsy (CP) or those with hypotonia are expected to move their fingers, hands, arms, head or body to create the music within AE. The child is not required to hold or touch any physical devices to create the music. When the child interacts with virtual objects via his movements, the virtual musical notes will disappear with appropriate acoustic feedback. The presence of adjustable dwell time and sensitivity of each note to move in this development prevent the sporadic involuntary movements during exercise. The pilot study results reveal that musical AE promote the visual-perceptual and motor planning skill. In the framework of decision making AE, there are a sequence of scenes such as topographical orientation, personal safety, personal preference and money management. The technology is decision making by brain injured adolescents to train their judgment. If the correct decision is being made at a given scene, the next scene will be appear to continue until the given task is finished. This will train the relearning of community mobility skills. However, the pilot studies disclose that there is no significant improvement compared to conventional therapy and this lead to the development of the wearable AE system for actual community excursions.

The alternative augmented reality based rehabilitation musical system has been developed by [148]. It was developed for children with CP to rehabilitate the arm movement via computer assisted music therapy. The rehabilitation aim is to improve the extension of arm exercises, flexion exercise of the wrist, repetitive motor training, visual perception exercises, auditory perception exercises and reproduction and development of more sophisticated music. The application was implemented based on augmented reality technique using colour markers which represent the keyboard for musical composition by users. The detecting of the coloured markers has been done by image processing via webcam. The positions of the coloured markers are calculated by computer graphics, visual computing and image processing techniques so as to render coloured virtual cubes. The flexibility of arranging the markers position allows the therapists to prepare motor planning for individual patients. The developed system is aiming to extend the conventional rehabilitation process and not to replace it. Therefore, this system is only for additional training of relearning cognitive, motor, psychological and social activities. The detail comparison of the literature can be found in Appendix A1.

2.7. Biosignal in Rehabilitation

Another rapidly advancing area of technology for rehabilitation is the application of the individual's own residual sensory and motor signals to augment function. In the context of biosignal, in this thesis, surface electromyography (sEMG) is used to record and manipulate in rehabilitation system.

2.7.1. Electrical Signals from Muscles – the Electromyogram (EMG)

The electrical signal associated with the contraction of a muscle is called an electromyogram (EMG). The study of EMGs, known as electromyography, provides the basic information of muscle activities such as contracting of the muscles, rate of tension build-up, fatigue, and reflex activities. Muscle is made up of many motor units, and each is controlled by a motor neuron through special synaptic junctions called motor end plates. Muscle activation is initiated by an action potential that travels along an axon and is transmitted across the motor end plates in to the muscle fibers, resulting in muscle twitch. The schematic diagram of the basic motor control mechanism is shown in Figure 2.8.

EMG electrodes usually collect the muscle electrical activity from these muscle fibers by means of either surface electrode or concentric needle electrode. Surface electrodes are attached to the patient's skin while concentric needle electrodes are inserted through skin into muscle tissue to detect the abnormalities and activation level of human movement by analysing the shape, size, and frequency of the motor unit action potentials generated by muscle fibers. Komi [149] has reported EMG amplitude increased tension during muscle lengthening, eccentric contraction and remained constant in spite of decreased tension during shortening, concentric contraction. During muscle fatigue, EMG measurements increase in amplitude and decrease in its frequency spectrum. In rehabilitation field, sEMG can be utilized in two forms: controller and biofeedback.

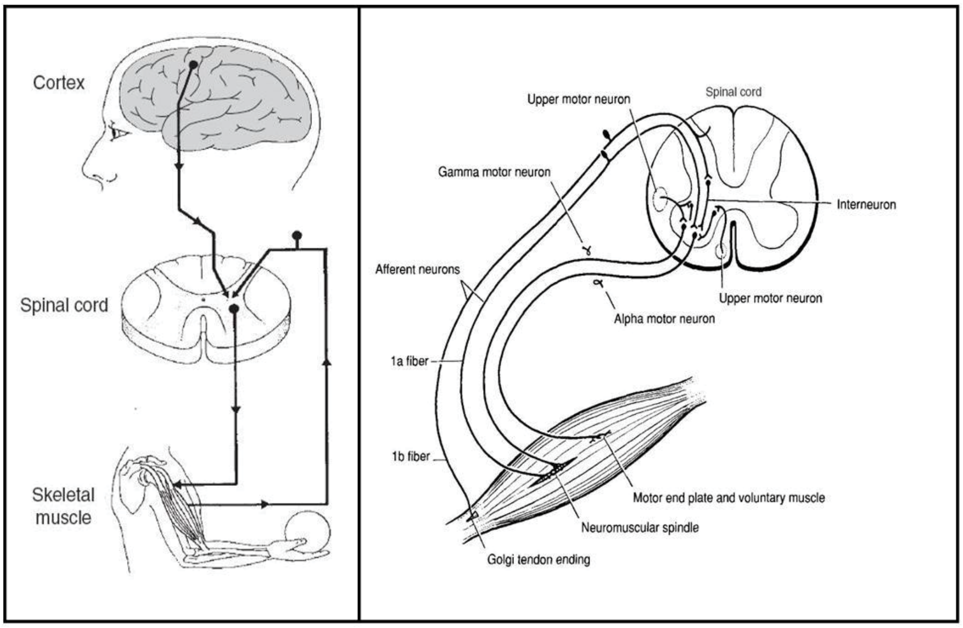


Figure 2-8: Schematic representation of basic motor control mechanisms and its components

2.7.2. Biosignal Driven Rehabilitation Systems

In general, the amplitude of the sEMG signal reflects the muscles activity levels which are related to the motion intention of the human. Therefore, the signals may detect the human intention of movement in real time. Based on this property, researchers have proposed several approaches to control the rehabilitation system to achieve the user intended motion.

One of the available approaches to study the human movement based on human intention is EMG-based forward dynamics. Several studies have been done to estimate moments about the knee [150], wrist [151] and elbow [152]. However, the developed forward dynamics algorithm faced several difficulties such as estimation of muscle activation due to high variability in EMG signals especially during dynamic conditions and transformation from activation to muscle force. These algorithms are based on phenomenological model [153] which is derived from Hill's classic work [154], biophysical model of Huxley [155, 156] or Zahalak's models [157-159]. To overcome these difficulties, optimization methods were used to predict the muscle forces directly by selection of muscles that will maximize jumping height or minimize the metabolic energy have been used in forward dynamic models [160, 161]. However, optimization-based models are only able to predict forces and they do not account for differences in an individual's neuromuscular control system. Thus, [162] developed four step models to estimate the forces and joint moments and movements from measurements of neural command. First step accounted for muscle activation dynamics and the input to the model is neural command (EMG) which will specify the magnitude of muscle activation followed by the second step of determining the muscle contraction dynamics. Third step characterise the musculoskeletal geometry followed by the final step of equation of motion that permit joint moments to transform muscle forces to joint moments.

Another prediction method was developed by [116]. In his system, myoprocessor algorithm was proposed to extract the predicted muscle moments generated by the muscles on the elbow joint based on the algorithm implemented by [163]. First, developed algorithm for estimating the normalized muscle activation level (NAL) obtains the raw EMG signals from patient's muscles and then this passes through high-pass filter followed by full signal rectification. The result which is an absolute value will then feed into a low-pass filter and finally will perform the signal normalization to achieve muscle activation level. Myoprocessor algorithm which solved the Hill-based state equation was implemented in the direct modelling approach in which muscle activation levels along with joint kinematics were fed into myoprocessor to obtain the muscle moment. The moment-based control system was developed and integrated with myoprocessor to control the exoskeleton.

Alternative sEMG based intention control system of articulated rehabilitation robot [164] is based on position and torque controller method. In his development, PID controller was used as a positional controller to minimize the position error between current position and target position. Impedance controller as a torque controller is used to measure the force interaction between rehab-robot and human arm to achieve human volition movement. EMG signals were extracted and processed via customized algorithm to select either active mode in which robot arm is driven by patient or passive mode which is driven by predefined motion trajectory. However, several literatures have pointed out that by using of positional feedback control it is difficult to assess patient's muscle condition. Therefore, sliding mode control was implemented and proposed by [83]. The concept of the new algorithm was to reduce the effect of chattering due to holding of sliding surface with infinite frequency. It was realized by replacing the discontinuous term with continuous approximation and adding the saturation function to realize this effect. The complete control system included data acquisition module, signal processing module, EMG to torque conversion to estimate the joint torque and send to sliding mode control.

In addition, user's intention is able to predict from sEMG by means of machine learning approach. In the development of [109], the intended movement of the human was achieved by fuzzy control. In his control system, there were three controllers: force sensor-based controller (FBC), EMG based controller (EBC) and obstacle avoidance controller (OAC) to become a total automatic power-assist controller. FBC was carried to make the generated wrist forces become zero and the output torque was input for shoulder and elbow joint of the exoskeleton. In the EBC, multiple neuro-fuzzy controllers were used to detect the intended movement of the user. The control was carried out based on muscle activity level: EBC was activated when the user's muscle activity level was high; otherwise control was taken over by FBC. Collision between the exoskeleton arm and frame of the wheelchair on which the exoskeleton was mounted were avoided by integrating with OAC. Another method, Fuzzy-Neuro control method with sEMG signals is proposed by K. Kiguchi et al.[126]. In his development, the exoskeleton employed fuzzy-neuro controller to assist shoulder joint motion based on surface electromyography (sEMG). However, the muscle activity level and each muscle activity of individual are different. Therefore, adaptive neuro-fuzzy controller was developed to adapt itself to the user's EMG levels [165]. The adaptive neuro-fuzzy controller used the error back-propagation learning algorithm to minimize the amount of evaluation function.

2.7.3. Control Algorithms in Rehabilitation Systems

Although various control algorithms are available to drive rehabilitation systems, Artificial Neural Network (ANN) is the most popular and effective technique with low computation cost. In this section, ANN based control methods is detailed. It is defined as a family of statistical learning models inspired by biological neural network. It is used to approximate the functions based on a large number of inputs which are generally unknown. In biological neural network, neurons receive electric and chemical signals via synapses located on the dendrites or membrane of the neuron. When strong signals are received above a certain threshold, the neuron is activated and emits a signal to the axon. This signal will be sent to another synapse and activate other neurons as shown in Figure 2.9. By mimicking the idea of biological neural network, ANN is made up of inputs which act as synapses, the weights which detect the strength of the respective signals by computing the mathematical function to determine the activation of the neuron, another function to compute the output of the artificial neuron as shown in Figure 2.10. In ANN, the weight

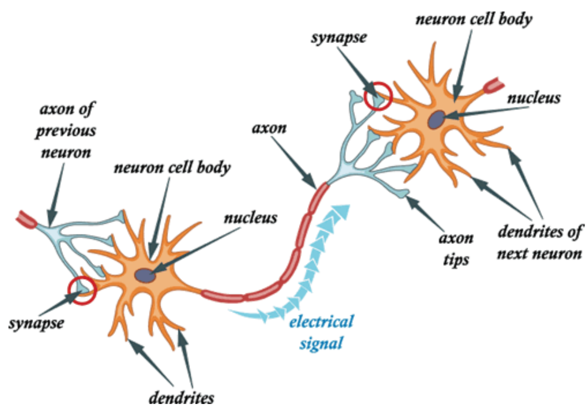


Figure 2-9: Biological neural network

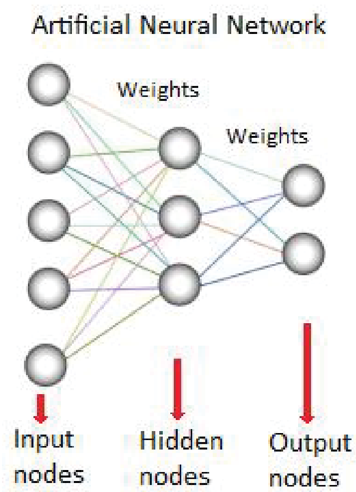


Figure 2-10: Artificial neural network

plays a major role as depending on the weight, the computation of the neuron will be different. The higher the weight of an artificial neuron is, the stronger the input which is multiplied by it. By adjusting the weights of an artificial neuron, the output can be obtained as desired. This process of adjusting the weights is called learning or training. The learning is executed by providing the training set consisting of a group of examples from which the neural network can learn. These examples are also known as training patterns that are represented as vectors which can be taken from images, signals, sensor data, arm movements and so on.

Supervised learning is the most common training scenario during which the network is presented with the input pattern together with the target output for that pattern. The target output usually consists of the correct answer or correct classification for the input pattern. In response to these input-output paired examples, the ANN adjusts the values of its internal weights. If the training is successful, the internal parameters are then adjusted to the point where the network can produce the correct answers in response to each input pattern. Generally the set of training examples is presented many times during training to allow the network to adjust its internal parameters gradually.

Although several regression or prediction models such as support vector machine (SVM), regularized least squares linear regression model (OLS) and physiological based model (PBM), the literatures have proven that ANN provides better prediction accuracy than other prediction models [166]. Therefore, in this thesis, ANN based prediction model is chosen to predict the shoulder joint angle. There are two famous regression models in the ANN context which are BPNN based regression model and ELM based regression model which will be compared and analysed in this thesis.

2.7.3.1. Back Propagation Neural Network (BPNN)

Back propagation (BP) was originally introduced by Bryson and Ho in 1969 [167] and it was independently rediscovered by Werbos in 1974 [168], Parker in mid 1980's [169] and PDP group in 1988 [170]. BP algorithm is a method to train or teach the ANN. It utilizes the mean square error and gradient descent to realize the modification to the connection weight of network. The modification to the connection weight of network is aimed at achieving the minimum error sum of squares and the training begins with random weights. The BPNN algorithm employs supervised training as the example inputs and outputs are provided to train the network and then the error is calculated. In general, BP learning algorithm can be decomposed into three steps: (1) forward propagation (2) backward propagation and (3) weight updates.

In the case of forward propagation, the input signal is propagated from the input layer, via the hidden layer, to the output layer. During this propagation, the weight and offset value of the network are maintained constant and the status of each layer of neuron will only exert an effect on the status of the next layer of neuron. If the expected output cannot be achieved as targeted output in the output layer, it will be switched to the backward propagation of error signal which is the difference between the real output and expect output of the network. In the backward propagation, the error signal is propagated from the output end to the input layer in a layer-by-layer manner. During the backward propagation, the weight value of network is regulated by the error feedback. The continuous modification of weight value and offset value is applied to make the real output of network closer to the expected output. The detail mathematical models of such propagations and weight updates are explained in chapter 4, section 3.

2.7.3.2. Extreme Learning Machine

Extreme learning machine (ELM) is similar to the BPNN but with a generalization of single-hidden layer feedforward networks (SLFNs) in which the hidden layer's nodes implement the random computational process and are not required to be tuned [171]. In contrast to the traditional learning algorithms, it provides not only the smallest training error but also the smallest norm of the output weights that provides better generalization performance of the networks [172]. The algorithm has proven that it has higher scalability and less computational complexity, hence, it becomes the most attractive for nonlinear modeling [173]. The mathematical formulation of ELM is given in chapter 4, section 4.

2.7.4. Biofeedback

Biofeedback is also known as augmented or extrinsic feedback which provides the additional information beyond the naturally available sensory or intrinsic feedback from user's various intrinsic sensory receptors [174]. It is the technique that is able to provide the biological information to the patients in real time. It usually involves measurement of a target biomedical variable and relaying it to the user by means of one or two strategies:

- Direct feedback: measurement of heart rate where a numerical value is displayed on the device.
- Transformed feedback: the measurements are used to control an adaptive auditory signal, visual display or tactile feedback method.

Traditional biofeedback is presented to the patient and the clinician via visual displays, acoustic or vibrotactile feedback. However, recent development in rehabilitation is based on a virtual reality based system and hence providing a novel form of immersive biofeedback and realistic impression to the patient. The biofeedback measurements are frequently used in physical rehabilitation. sEMG biofeedback is a method of retraining muscle by creating new feedback systems as a result of the conversion of myoelectrical signals in the muscle into visual and auditory signals [175]. sEMG uses surface electrodes to detect a change in skeletal muscle activity, which is then fed back to the user usually by a visual or auditory signal. The sEMG biofeedback can be used to either increase activity in weak or paretic muscle or it can be used to facilitate a reduction in tone is a spastic one.

Therefore, sEMG biofeedback has been shown to be useful in both musculoskeletal and neurological rehabilitation. One of the pioneers, George Whatmore, in the use of surface Electromyography (sEMG) as a biofeedback tool highlighted how problems could emerge when an individual muscle performing efforts were too high or too low. He categorized a large number of representing efforts to describe in many ways in which person's emotions are reflected in the patterns of muscle activity [176]. The clinical applications in sEMG were studied in greater depth by Kasman et al. [177].

2.8. Summary

In this chapter, a background on the human nervous system and related trauma or diseases of the nervous system was given. The chapter considered the detailed literature review on the recovery methods due to these trauma or diseases through rehabilitation systems with current available technologies. Various technologies were utilized in rehabilitation environment in order to overcome specifically physical and cognitive limitations in the literature. However, it was found that there were certain limitations in the available rehabilitation systems and these were all pointed out in this chapter. Additionally, where possible the need for the contributions proposed in this thesis was justified. In the next chapters, these contributions are considered in more detail with the corresponding concepts, experiments and results.

Chapter 3
Augmented Reality based Upper Limb Rehabilitation System

3.1. Introduction

An important aspect of motor rehabilitation is what kind of approach to be conducted in order to achieve optimal functional outcome for fast and effective motor recovery. There are two types of approaches namely the traditional approach which employs direct neuromuscular re-education techniques and Task Oriented Therapy (TOT) approach. In general, traditional therapy only permits the use of compensatory behaviors rather than optimizing function within the context of maximal utilization of the impaired anatomy. Moreover, it places much emphasis on the impairment level of disablement without considering adequately the implications or relevance of voluntary participatory behaviors. In contrast to traditional therapy, TOT approach aims to achieve a goal or a task with consistency, flexibility, and efficiency. TOT is also known as a top-down approach or cognitive approach where the therapy emphasis is upon assisting a patient to identify, develop and utilize cognitive strategies to manage particular tasks more effectively [178]. Winstein and Wolf [179] proposed a minimum of three active ingredients for effective TOT to promote post-stroke upper limb recovery. First ingredient is ***Challenging*** that defines the therapy should provide challenge in attention to acquire new learning through solving the motor problem. Second ingredient is ***Active Participation*** that identifies that the therapy should motivate enough for active involvement and long term engagement. Final ingredient, ***Progressive and Optimally Adapted*** such that over practice, the task demand is optimally adapted to the patient's capability being neither too simple to not challenge enough nor too difficult to cause a low sense of competence. The evidence of long-lasting cortical reorganization of the corresponding areas in the brain being used due to TOT in motor rehabilitation has been shown in several clinical reports [180, 181].

This chapter starts with an introduction to therapeutic therapy in upper limb rehabilitation to understand its importance and effectiveness to post-stroke patients. Secondly, the design consideration based on biological targets and fundamentals of serious game design theory for fast recovery, motivation and repetitive training without losing interest are thoroughly analyzed. Thirdly, the importance of biofeedback in upper limb rehabilitation is discussed and fourthly, the significance of Augmented Reality (AR) in upper limb rehabilitation is detailed. Finally, the upper limb rehabilitation system, RehaBio system, is proposed and thoroughly explained in this chapter. The effectiveness of the development has been evaluated with Data Analysis, Performance Analysis and Questionnaire via non-clinical trials and the demonstration of the developed system has been performed in Port Kembla Hospital.

3.2. Design Considerations

The design of effective TOT for upper limb rehabilitation focuses on two main considerations: ***Biological Targets*** and ***Serious Games and Design Theory***. The former aims to induce neuroplastic adaptations in the CNS and reduce the alterations in skeletal muscles while the latter intends to provoke high levels of engagement and self-motivation.

3.2.1. Biological Targets

During the development of therapeutic exercise for motor rehabilitation, biological targets such as the central nervous system (CNS) and skeletal muscles are the most important factors to consider for cure at the origin of the disease. As stroke damages the central nervous system (CNS), it becomes the prime target for recovery in the context of motor rehabilitation. One of the properties in the organization of CNS allows for plastic recovery called ***Neuroplasticity*** which produces changes in neural pathways and synapses due to changes in behavior, environment, neural processes, thinking, emotions, as well as changes resulting from bodily injury. The adaptation of neuroplasticity in the CNS can be induced by conducting specific training therapies that offer multiple tasks to train attention and distractibility combined with a motivational approach offering rewards and emotional support. Therefore, TOT came into the picture as this is the most suitable therapy to achieve improvements in functional outcomes and overall health-related quality of life.

Another major concern as a result of stroke is disuse of skeletal muscles. Skeletal muscles are the voluntarily controlled actuators for movements by receiving neural commands from the brain via motor neurons. However, in stroke survivors, such neural commands are disturbed and muscle fibers do not receive any signals or very less signal from the brain for muscle contractions and this results in disuse of skeletal muscles. Disuse of skeletal muscle will eventually lead to muscle alterations such as muscular atrophy and increase intramuscular adiposity, fiber phenotype shift, and changes in muscle metabolism that could propagate disability [182]. To prevent such muscle alterations, TOT, which allows a wide range of motion should be introduced during motor rehabilitation.

After the biological targets are properly analyzed and defined, the next step is to define what kind of motivating technologies to employ for low esteem stroke patients.

3.2.2. Serious Game Design Theory

In general, stroke patients suffer from psychological effects and "***Depression***" is one of the most significant results for a person's post-stroke condition. This becomes one of the major concerns and an obstacle to rehabilitation. Therefore, motivation plays a major role while stroke survivors are in a rehabilitation program. It has been suggested that the integrating of games into rehabilitation therapy enhances patient motivation even for long term training with repetitive mode [127]. Among the various type of game systems, computer games are often highly engaging and addictive in nature; as a result this may therefore offer high quality motor rehabilitation.

Designing a computer game can be as simple as creating with just story, art and software. However, within the context of rehabilitation, a game should develop with pedagogy that makes a game serious: a serious game that allows the player to achieve specific skills through entertainment and engagement for rehabilitation purpose. They can be developed for any platform and can be of any genre as long as the content permits the user to develop the intended skills. There are three core concepts: *meaningful play*, *iterative design* and *challenge* that are essential for the development of serious games for motor rehabilitation.

Meaningful Play: The goal of a successful game design is the creation of meaningful play [183]. In a serious game, meaningful play emerges from the relationship between a player's action and the system's outcome where interaction is both discernable, a player can perceive how his action is affecting the game immediately via feedback and integrated, his action does not only have an effect instantaneously but also has an effect at the later stage of the game. In the context of player's actions, it is important to identify what kind of action is needed to deliver to the player as an upper limb rehabilitation exercise. These actions include shoulder flexion (SF), shoulder extension (SE), shoulder hyperextension (SHE), shoulder adduction (SAD), shoulder abduction (SAB), outward rotation (OR), inward rotation (IR) elbow flexion (EF), elbow extension (EE), forearm pronation (FP), forearm supination (FS), wrist flexion (WF), wrist extension (WE), wrist hyperextension (WHE), ulnar flexion (UF) and radial flexion (RF) as shown in Figure 3.1. Feedback in a serious game enables a player to measure his performance in achieving goals or progression in their skills over time. Hence, it is central to creating and maintaining meaningful play. Feedback can be in many forms such as visual, aural or/and haptic in a game. As far as feedback in rehabilitation is concerned, failure as a feedback from the player action can be an important issue as rehabilitation feedback should be to encourage and reward all engagement with success. Hence, it is very important to consider how to present motivated feedback in serious game. In general, stroke patients also suffer from cognitive disabilities; thus, it is important to show the feedback clearly and obviously.

Iterative Design: To achieve a rigorous and effective game design, an iterative methodology is required. This starts with fundamental game rules and core mechanics as it is impossible to fully anticipate the experience of the game. They can be only found out by way of play, for instance, seeing where it excels and where it grinds to a halt. During the process of designing the game, it is played, evaluated, adjusted, and played again, permitting improvement on the successive versions of the game which include aesthetic, understanding and ease of manipulation.

Game Challenge: Game challenge plays one of the major roles in rehabilitation exercise. This is to monitor the patient's performance as well as match the game level of difficulty to the patient's ability. In addition to that, the challenge of the game makes the user engage for a longer time in rehabilitation. To enable the optimal challenge, it is necessary to continuously adapt the game levels by matching the patient's existing skills without the feeling of depression or loss of interest.

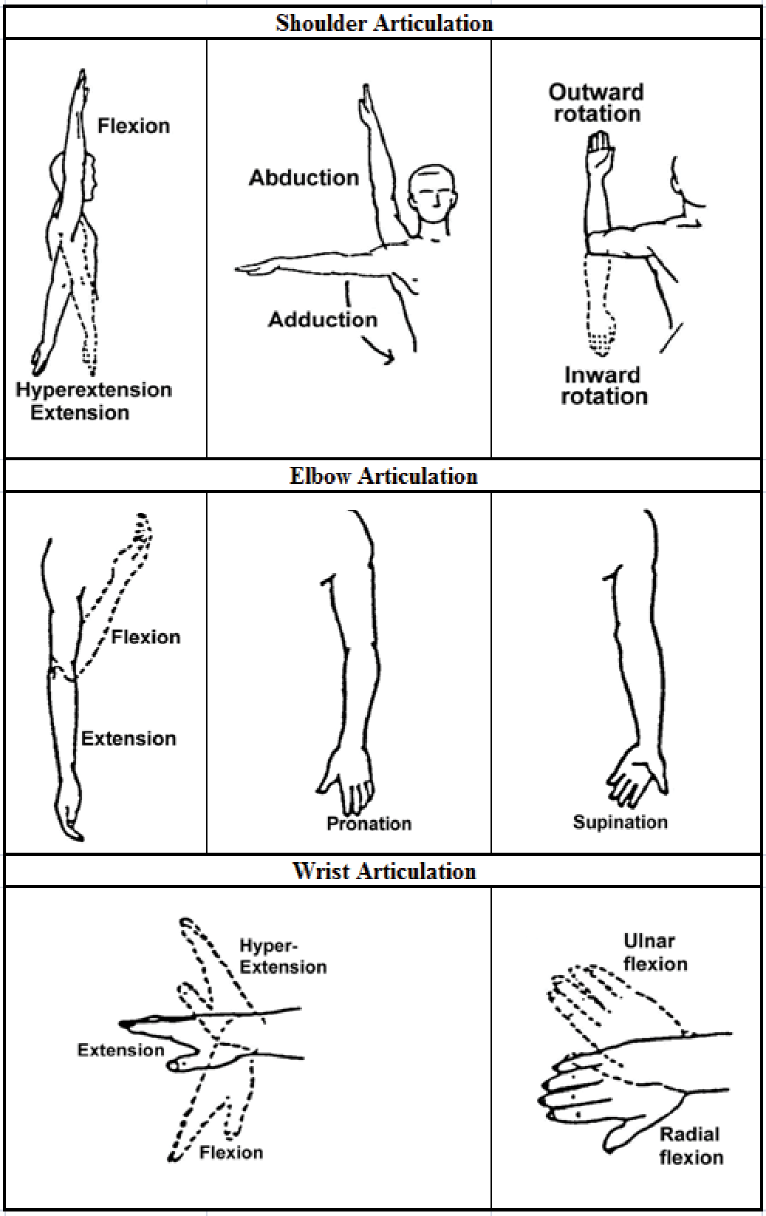


Figure 3-1: Human Upper Limb Articulations

3.3. EMG Biofeedback for Upper Limb Rehabilitation

Muscle dysfunction may be caused by many reasons, some of them having to do with pathology of muscle tissue, some of them are due to trauma or injury, and some of them having to do with patterns of use or misuse. One of the pioneers, George Whatmore, in the use of surface Electromyography (sEMG) as a biofeedback tool highlighted how problems could emerge when an individual muscle performing efforts were too high or too low. He categorized a large number of representing efforts to describe in many ways in which person's emotions are reflected in the patterns of muscle activity [184]. The clinical applications in sEMG were studied in greater depth by Kasman et al. [185].

The sEMG biofeedback techniques fall roughly into three clinical entities: down-training, up-training and coordination training. The down-training techniques are used to facilitate a reduction in muscles which are overactive. Up-training is to learn how to turn on a particular muscle or muscle group. It is commonly conducted when working with inhibited muscles, or muscles that have been weakened due to disuse or injury. Coordination training is considered an advanced level of training and usually follows successful up- or down-training. This will teach the patient how to obtain the correct balance of agonists or antagonists. However, this is difficult due to cooperation of muscles involves in all three domains: posture, movement and emotions. The common techniques that are used to train the muscles are isolation of target muscle activity [186], relaxation-based down-training [187-189], threshold-based up-training or down-training, threshold-based tension recognition training [190] and sEMG-triggered neuromuscular electrical simulation[191]. It has been proven that integrating with biofeedback system provides improvement in retraining of muscles strengthening and improves motor skills [192, 193].

A key factor in promoting recovery of motor function is the degree of sparing of the contralateral sensorimotor cortex and corticospinal tract [105, 194]. By integrating the sEMG biofeedback in rehabilitation therapy, the sensory information returning to the somatosensory area may assist in establishing voluntary movement control associations with the adjacent primary motor cortex [72]. In addition to this, functional recovery can be facilitated by visually substituting for impoverished proprioceptive input from the paretic limb [195]. The action and perception involved in executing voluntary movements activates the neural mechanisms in the association areas of the cerebral cortex, and these association areas integrate sensory and motor functions [72]. Therefore, sEMG biofeedback plays an important role not only in induction of neural plasticity but also in motivational aspect [20].

3.4. Augmented Reality for Upper Limb Rehabilitation

Aforementioned in literature, augmented reality is increasing research interest in many clinical applications due to its simplicity and motivating ability especially in the rehabilitation field with multi-disciplinary fusing technologies of computer vision, wireless communication, etc. In the context of rehabilitation, AR offers the advantages of being able to use real objects to interact within virtual environments or games. These real objects can vary in size, shape and mass which may result in players acquiring muscle strength and motor skills which are more transferable to everyday life than those associated with activities in pure virtual environments, where the user is typically not holding any physical object. In addition to this, AR allows the players to see the live view of real world environment, augmented by computer-generated imagery which is virtual object. There are six key ingredients to include while developing any AR environment. These ingredients include AR application, content, interaction, technology, the physical world and participant(s).

3.4.1. AR Applications

It is important to know how to develop a good AR application and there are two core questions for this as follows:

1) What makes a good candidate for an AR application?
2) What makes a good AR application?

The first question refers to how well matched the candidate application is to the affordances offered by AR whereas the second one addresses how well the AR application is executed and meets the needs of the user of the application. In the context of affordances, AR allows one to superimpose digital information onto the real world in such a way that the user perceives the digital information as part of the real world. Keeping these affordances in mind, then, a good candidate for an AR application is one that exploits those affordances in a positive way to solve a problem of one sort or another. For the second question, to be able to accomplish a good AR application, it is important to perform an evaluation to find out what aspects of an application are working, what are not, why that is, and how to remedy or improve on it. The evaluation can include "Does the application fulfill the goal that drove the creation of the application?", "Is the target audience actually using the application and using it in an effective way?" and "Is AR the right medium to use for the application?" . In this way, an effective and enjoyable AR application will be achieved.

3.4.2. Contents

"Contents" in an AR environment is vital to any AR applications. It refers to all the elements in the virtual world which interact with the user to provide an augmented reality experience. There are many different types of content and different ways to represents that content in AR environment. It can be the *representations that are perceived by our senses*, *the differentiation between the real world and virtual world*, *realistic representation vs abstract representation*, *representations meant to convey physical attributes vs representations to communicate emotion* and *the idea of representing content to tell a story*. Without good content an AR application is nothing more than a technological novelty. Therefore, the contents of the AR application must work together to communicate the desired content to the users, and their actions must communicate to the AR application their intent and goal.

3.4.3. Interaction

In Augmented Reality, interaction plays a key role in the overall user experience. There are a number of interaction methods by which a user can communicate with the virtual world, AR application, or other user in the experience by means of physical buttons, keys, sliders, or any other manipulators to interact in an AR experience. In the context of the virtual world, the interaction can be direct user control in which a user manipulates the virtual world in a manner that is directly analogous to how they do it in the physical world, physical control where users use a physical device that they can hold and touch, virtual control such as virtual button that users can manipulate in the virtual world and agent control where users issue commands to some agent in the VR world to carry out the action on behalf of the users.

3.4.4. AR Technologies

In Augmented Reality (AR) every experience involves several technologies such as computer vision technology to track the location and orientation of virtual objects, some form of computation to integrate the virtual elements of the experience with the real world, some mechanism to display the virtual elements of the experience and some techniques or engine to detect the collision between virtual objects.

3.4.4.1. Objects Tracking in AR

Augmented Tracking of virtual object is one of the most important tasks in computer vision applications such as motion based recognition, video games, human computer interaction, automated surveillance, traffic monitoring and vehicle navigation. However, the tracking can be limited due to loss of information caused by projection of virtual

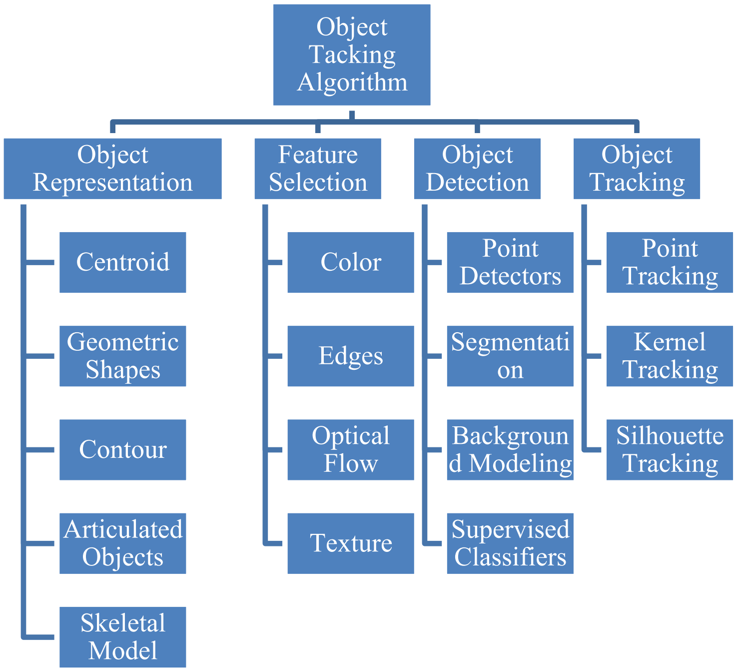


Figure 3-2: Different Categories for Object Tracking Algorithm

objects in 3-Dimension world, complex object movements, partial or full object occlusions, complex object shapes and real-time processing requirements. Therefore, numerous tracking approaches to tackle these limitations have been proposed according to the block diagram in Figure 3.2.

There are four main categories to consider for detecting the objects in the scene [196]. They are *object representation*, *feature selection*, *object detection* and *object tracking*. *Object representation* is to represent their shape and appearance. It can be point or centroid, geometric shapes such as rectangle, ellipse, etc, boundary of an object, articulated objects in which body parts are held together with joints and skeletal models as shown in Figure 3.3.

Feature selection plays a major role in tracking as this will distinguish the uniqueness of the objects in the feature space. Feature selection can be based on colors, edges, optical flow or texture depending on the application domain. In color feature selection, RGB (Red, Green, Blue) where dimensions are highly correlated, **L*u*v** (***L*** for lightness, ***u*** and ***v*** for the calculated values from chromaticity coordinates) and **L*a*b** (***a*** and ***b*** for the color-opponent dimensions) which are perceptually uniform color spaces and HSV (Hue, Saturation, Value) color space which is an approximately uniform color space are available for tracking. Edges feature selection is able to identify the changes in image intensities and it is less sensitive to the illumination changes compared to the color features [197]. Optical

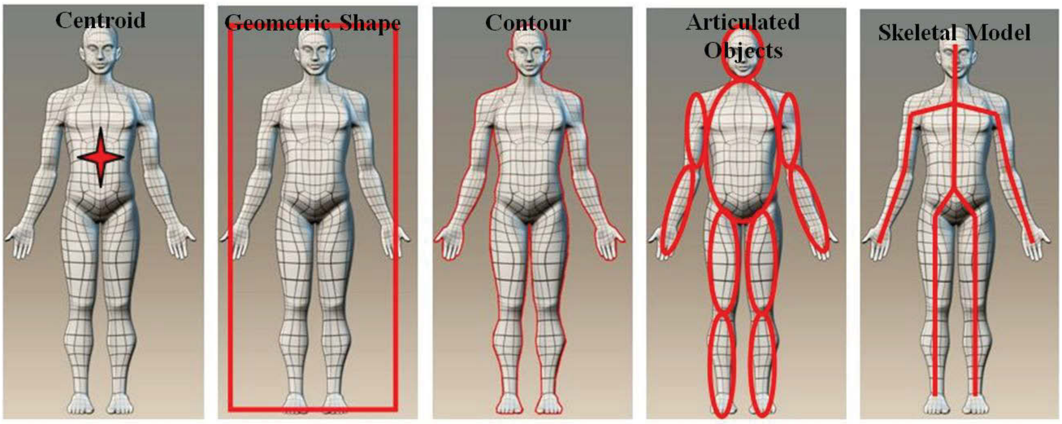


Figure 3-3: Object representation

flow in feature selection is computed based on the brightness constancy of corresponding pixels in consecutive frames [198]. Texture feature selection is a measurement of the smoothness and regularity and this requires processing step to generate the descriptors such as steerable pyramids [199], wavelets [200], etc.

Object detection mechanism is required in every tracking method. Generally, single frame information approach is used in object detection. However, temporal information from a sequence of frames is used in some object detection methods to reduce the false detections. The popular detection methods include point detectors [201], segmentation [202], background modelling [203] and supervised classifiers [204].

Point detectors are used to locate the point of interest in images which have an expressive texture in respective localities. Segmentation method is the process of partitioning the image into multiple segments to simplify and make it easier to analyze. To be more exact, segmentation is the process of assigning the same label to the pixel that shares certain characteristics in an image. Background modelling is the object detection method that is based on finding deviations from the model for each incoming frame. If there is any significant change in an image region from the background model, it signifies a moving object. Supervised classifiers method is achieved by learning different object views automatically from a set of examples by means of learning mechanisms such as neural network, support vector machines and adaptive boosting.

Object tracking is to create the trajectory of an object over time by locating its position in every frame of the video. This can be achieved via point tracking, kernel tracking or silhouette tracking method. Point tracking method detects the object in consecutive frames by points and it can be further divided into two methods: deterministic method [205] which uses qualitative motion heuristics and probabilistic method [206] which takes the object information and uncertainties into account to establish the correspondence to tackle the occlusions, misdetections, objects' entries and exits problems. Kernel tracking is achieved by computing the motion of the object which is generally in the form of parametric motion such as translation, conformal, affine, etc or dense flow field computed in subsequent frames [207]. Silhouette tracking method [208] is to provide the accurate shape description for the objects with complex shapes and to find the object region in each frame by a color histogram, object edges or the object contour by the previous frames.

However, assumptions are made to constrain the tracking problem in the context of a particular application. These can be minimal amount of occlusion, high contrast with respect to background, illumination constancy, smoothness of motion, etc. To minimize such assumptions, a customized tracking algorithm has been developed for RehaBio system which is part of the contributions of this thesis.

3.4.4.2. Collision Detection in Augmented Reality

Collision detection is essential in many applications such as computer games, physical simulations, robotics, virtual prototyping and engineering simulations to ensure realistic appearance. In AR environment, collision detection is one of the essential aspects to generate on how the interaction between the virtual objects and real objects which capture by webcam occurs. It is generally refers to detecting of a seemingly simple problem: detecting of two or more objects which are intersecting. More specifically, collision detection concerns the problems of determining whether or not the objects intersect, when the collision will occur or has already occurred and how the objects are coming into contact each other. To answer such questions efficiently, the collision system or algorithm should be designed by considering several factors such as *application domain representation*, *different types of queries*, *environment simulation parameters*, *performance*, *robustness* and *ease of manipulation and us*e [209].

***Application domain representation*:** The geometrical representations such as polygonal representation or constructive solid geometry representation of the scene and its objects play the important role in developing the collision detection algorithms. In any AR environment, it is possible to pass rendering geometry directly into the collision system; however, it is better to have separate geometry to simplify and speed up the detection. In addition to that, it is also often wise to provide specialized collision systems for specific scenarios rather than having one all-encompassing collision detection system.

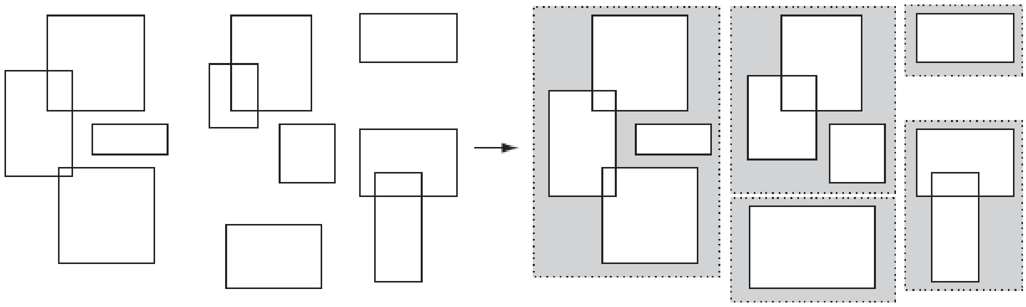


Figure 3-4: Broad Phase

***Types of Queries*:** Interference detection or intersection testing are the most straightforward collision queries in the AR experience. This is to check whether two static objects are overlapping at their given positions and orientations.

***Environment Simulation Parameters*:** There are several parameters of a simulation that have a direct effect in collision detection system such as how the number of objects and how the objects move relate to collision processing. Higher number of objects in AR experience will become expensive and hence it will require speeding up the process by reducing into two phases: the broad phase and the narrow phase. Broad phase identifies the smaller groups of objects that have potential of colliding and excludes those that definitely are not, are as shown in Figure 3.4. The narrow phase is responsible for determining the exact collisions by performing the pairwise tests within the subgroups. Another factor that can affect computational effort and accuracy of the detection is depending on the type of motions which are discrete (static collision detection) and continuous motion (dynamic collision detection). Static collision detection is detecting the intersection between the objects which are stationary at their current positions with zero velocities. In contrast, dynamic collision detection considers the full continuous motion of the objects over the given time interval which can detect the exact time of collision and the point of first contact. However, these tests are much more costly than static tests. Therefore, it is important to choose a proper detection test to suit AR application.

Performance: It has been suggested that the best possible visual games must run at 60 fps. Therefore, the processing time for collision detection may only allow for a few micro seconds and this is where speed optimization comes into the picture for faster processing in the collision detection system. One of the inexpensive optimization methods is performing the *bounding volume* tests which will be discussed in the following section.

Robustness: Robustness in an AR application refers to a program's capability of dealing with numerical computations and geometrical configurations. The former problems arise from the use of variables of limited precision during computations while the latter problems arise from topological errors and overall geometrical inconsistency that lead to the unreliable numerical calculations. Therefore, to avoid such runtime errors, robustness should be considered throughout both design and development of the collision detection system.

Ease of Implementation and Use: It is important to look into the overall complexity as well as how many and what type of special cases are involved, how many tweaking variables are involved, how much time is required in the build process to construct the collision-related data structures and how often the model changes throughout the development. All of these important points define the implementation complexity and manipulation in AR experience, therefore, it is very important to consider these points properly while developing a fast and effective collision detection system for specific AR application.

3.4.4.3. Bounding Volumes (BV)

Direct collision detection testing based on geometry is often very expensive, especially if there are hundreds or thousands of polygons. To minimize such cost, bounding volumes (BV) are usually tested for overlap before the geometry intersection test is performed. It is a single simple volume encapsulating one or more objects of more complex nature and it allows for fast overlap rejection tests as shown in Figure 3.5. In some cases the collision can be determined by the BV of the object itself.

Many geometrical shapes have been suggested as bounding boxes. However not all the

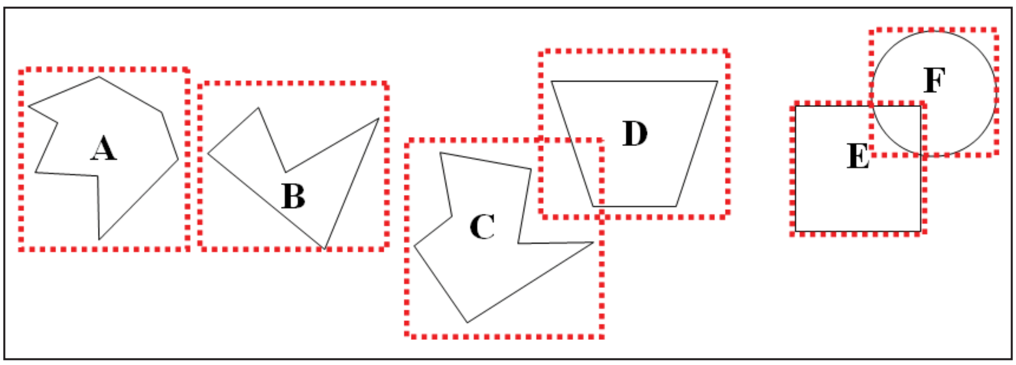


Figure 3-5: Overlap rejection test between Bounding Volume

geometric objects have effective bounding volumes and only if the BV has a simple geometric shape with the following properties: inexpensive intersection tests, tight fitting, inexpensive to compute, easy to rotate and transform, use little memory and will provide the less expensive test. Some of the most common bounding volume types are illustrated in Figure 3.6. The figure also depicts the level of faster detection test with less memory and more precise bound.

Sphere Bounding Box: The sphere is the common type of bounding volume that has an inexpensive intersection test with most memory-efficient bounding volume. It also has the benefit of being rotationally invariant, which means that they simply need to be translated to new position. Sphere bounding boxes are defined in terms of a center and a radius.

AABBs: The axis-aligned bounding box (AABB) is one of the most common bounding volumes. It is rectangular in shape, six-sided for 3D and four-sided for 2D objects. AABB are aligned with both X and Y axis and are un-rotatable. The best feature of the AABB is its fast overlap check, which simply involves direct comparison of individual coordinate values.

OBBs: Oriented bounding box (OBB) is very similar to AABB but with an arbitrary orientation. Therefore, there are many possible representations for an OBB. The most common representation is a centre point plus an orientation matrix and three halfedge lengths which are based on the separating axis theorem.

Sphere-swept Volumes: These bounding volumes are in a cylindrical shape and of course the overlap tests for these are quite expensive due to complex mathematical

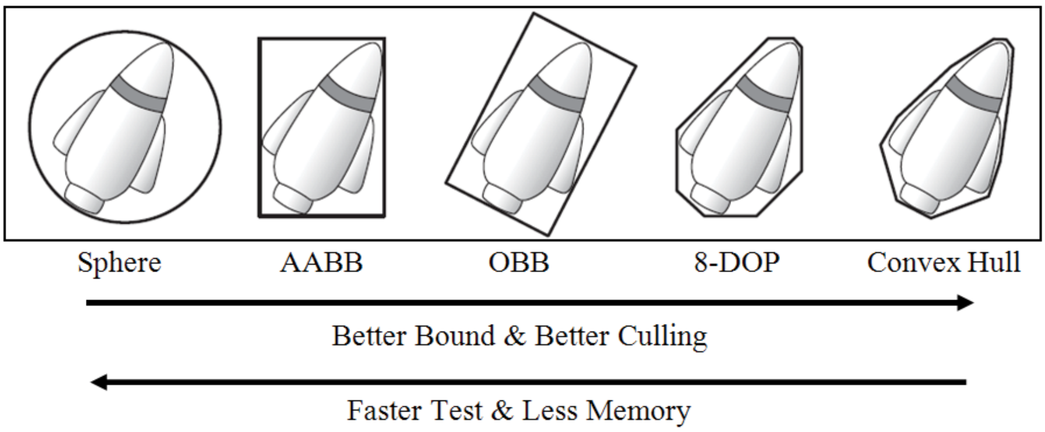


Figure 3-6: Common Types of Bounding Volumes

calculations. However, if the object of interest is cylindrical in shape, cylinder volume becomes a more attractive bounding volume. The cost of the test is totally dependent on the cost of the distance function. To make the test as inexpensive as possible, the inner primitives are usually limited to points, lines or rectangles resulting in sphere-swept points (SSPs), sphere-swept-lines (SSLs) and sphere-swept rectangles (SSRs) respectively. These sphere-swept volumes are illustrated in Figure 3.7.

k-DOPs: Discrete-orientation Polytopes (k-DOPs) are convex polytopes with general number of dimensions “k”. For instance, 8-DOP has faces aligned with the eight directions as depicted in Figure 3.6. The overlap test for k-DOPs is much faster than OBB overlap test due to the fixed direction planes and the memory requirement for an OBB is equivalent to a 14-DOP. This test is the best when few dynamic objects are being tested against many static objects. However, the major drawback of the k-DOP is that even if the volumes are rarely colliding the k-DOP must still be tumbled or updated.

Convex Hull: Except from the sphere, most of the bounding volumes are convex polyhedral which are representable as the intersection of a set of halfspaces. For example, AABBs and OBBs are both the intersection of six halfspaces. It provides better fitting results if there are more halfspaces as shown in Figure 3.6. However, with more halfspaces, the test becomes more expensive, computationally complex and takes large amounts of memory to represent.

In addition to these BV, there are two collision detection methods: ***discrete*** and ***continuous***. In the discrete collision detection method, the objects’ positions are updated in every frame and then checked for interpenetration or contact. The continuous collision

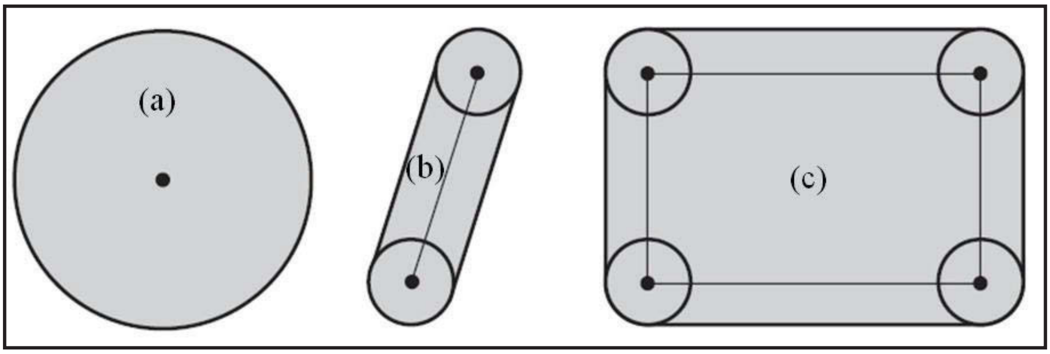


Figure 3-7: Sphere-swept Volumes

detection is a method to prevent interpenetrating from each other. Such detection methods are shown in Figure 3.8.

In any collision detection method, it is important to know how much of the two bodies have already penetrated into each other and this can be defined by several cases based on Circle, Axis Aligned Bounding Box (AABB), Oriented Bounding Box (OBB) and Polygons. It can be Sphere vs. Sphere, AABB vs. AABB, Sphere vs. AABB, Sphere vs. OBB, OBB vs. OBB and Poly vs. Poly. Among the possible collision cases, AABB vs. AABB has been chosen to check for necessary collision detection in developed exercises due to their fast detection and less memory usage.

3.4.5. The Physical World

The physical world is the place in which every AR experience takes place. This is taken by the camera and displayed in real time and the virtual objects are laid on top to create the AR environment. For instance, AR experience is to display the cat on top of the desk. However in reality only the desk is available which is in real physical world and the (virtual) cat is added onto the physical world to create the desired AR experience.

3.4.6. Participants

The role of AR technology is to provide the artificial stimuli to cause the participants to perceive that something is happening that really is not. Participants in AR environment have an active role in AR experience as all of their motions, activities and actions affect how the system responds. Therefore, they are the ones that can evaluate how good or bad the AR experience is. If there are multiple participants in one AR experience, the

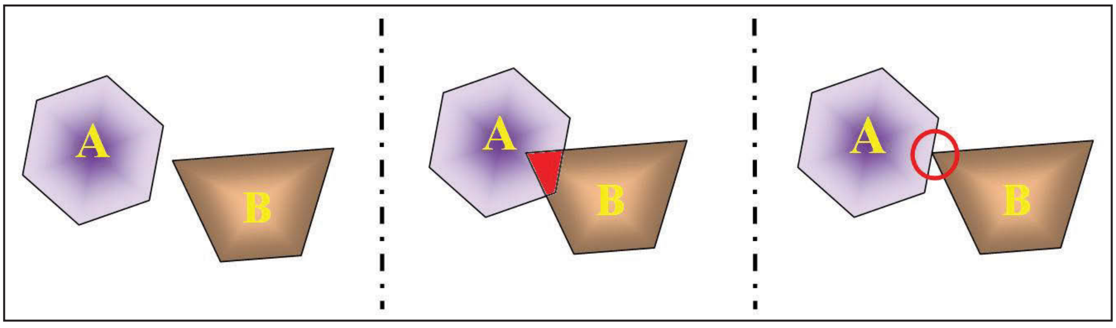


Figure 3-8: Collision Detection Methods

interaction will be more complex to develop.

3.5. Thesis Contribution-1: Augmented Reality based RehaBio System

The first contribution of this thesis is detailed in this section which is the development of low cost home based upper limb rehabilitation exercises with real time biofeedback simulation. The developed system is integrated with motivational upper limb rehabilitation exercises to surpass the boring traditional exercises and biofeedback to stimulate the nature of human brain plasticity for fast recovery. The results of this work had been published in [210, 211]. The system is named as a RehaBio which stands for ***Rehab***ilitation system with ***Bio***feedback simulation. After all the important ingredients have been thoroughly considered and defined as previously mentioned, the architecture of the RehaBio system is organized and developed as depicted in Figure 3.9. The system is incorporated with game based upper limb therapeutic exercises and real-time active muscle simulation to motivate the patient interest for long term therapy. The complete system consists of three modules: Input, Framework and Output module. The input module consists of hardware devices while the framework module is RehaBio software development which is constructed by several sub-modules that communicate the commands among each other. The last module, the output module, of the system is a monitor display in which the final display of virtual objects and augmented environment with interaction and feedback are presented.

3.5.1. System Input

In RehaBio input, there are three main components which are USB webcam, color markers

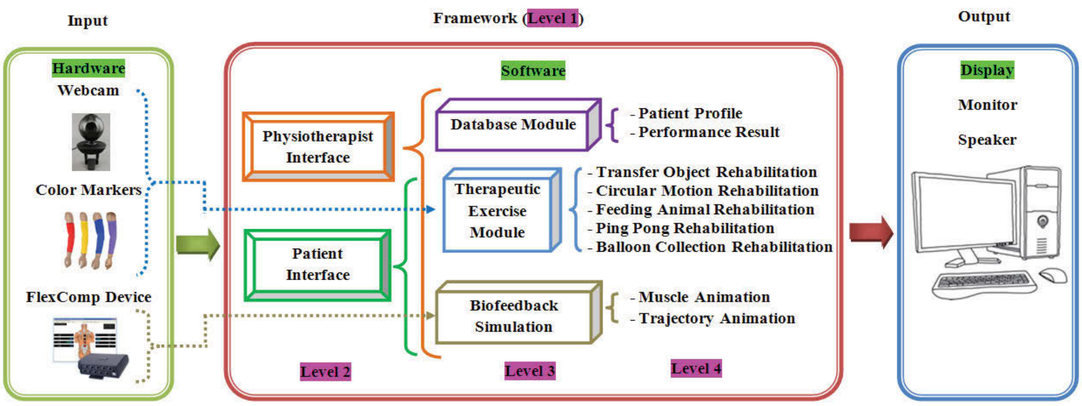


Figure 3-9: Architecture of RehaBio System

and EMG acquisition device for the system to commence. The first component: USB webcam is a 2-megapixel Logitech Webcam C600 with standard RGB colour space profile. This is used to capture the real time video image background to create the AR environment. As for the second component, colour markers, it can be any wearable glove or cloth with a different colour from the background so that the webcam will be able to track in real time easily. These markers are attached to the shoulder, elbow, hand and finger for manipulation of the virtual objects in AR environment. The colour marker in the RehaBio system serves as two-fold manner: one is responsible for tracking the current position of user's arm and the other purpose is to manipulate the virtual objects in AR environment. The tracking is executed by custom built ***Colour Tracking Algorithm*** while manipulation of virtual objects is executed by custom made ***Collision Detection Algorithm***. The third component, data acquisition device, is used to collect the EMG data by FlexComp Infiniti™ System from Thought Technology [212] with four EMG MyoScan™ T9503M Sensors which are attached to the user's upper limb muscles.

3.5.2. System Framework

The overall framework (Figure 3.9) of RehaBio system consists of level 2 sub-module which is made up of ***Physiotherapist Interface*** and ***Patient Interface*** to access the level 3 sub-modules: ***Database Module***, ***Therapeutic Exercise Module*** and ***Biofeedback Simulation Module*** (Figure 3.10). The ***Physiotherapist Interface*** allows the therapist or

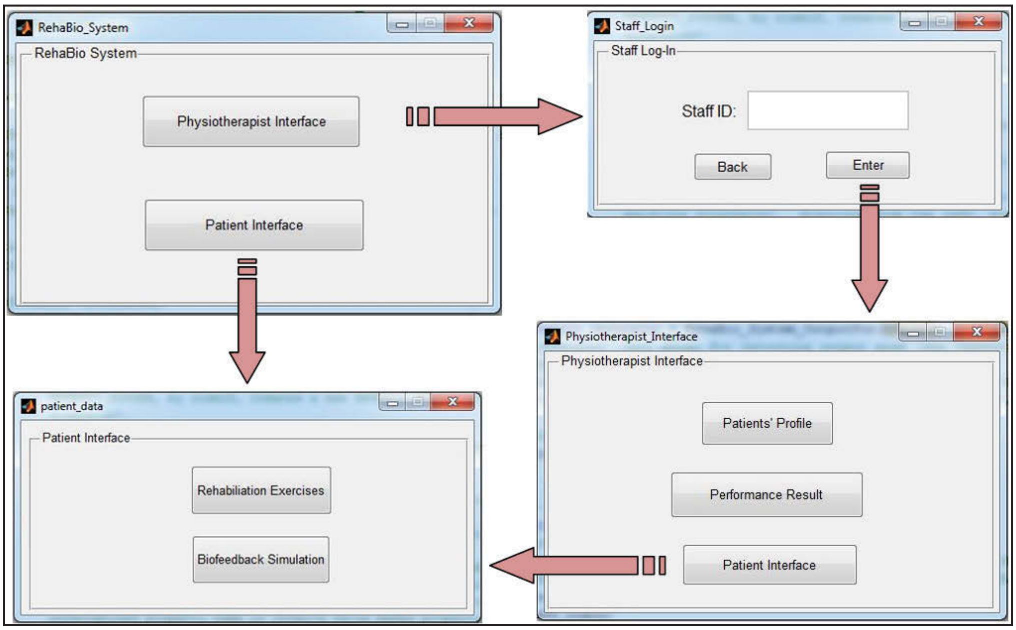


Figure 3-10: The GUI of RehaBio system (Level 2 & Level 3)

carer to access and edit the patients' information and medical records, therapeutic exercises and biofeedback module while ***Patient Interface*** only allows for the patient to access the exercises and biofeedback module.

3.5.2.1. Database Module

Database module is where patient profiles and training information are stored to track the patient performance along the rehabilitation period. This module is a restricted module which only can be accessed by registered physiotherapist or carer by entering their staff identification (ID) number into the system. It stores all the information of old and current patients' particulars and by choosing an appropriate patient's name from the drop down list, respective patient's particular and clinical information such as history of EMG threshold level throughout the rehabilitation process, training sessions with respective date will be displayed. This is also the place that new patients' information is registered and recorded. After the particular patient's clinical data has been reviewed, therapist/carer is able to decide on an appropriate new EMG threshold level to set and exercise for that patient for the next appropriate training. Once the new EMG threshold level has been set, the new value will be updated in several places such as ***Database Module*** and ***Biofeedback Simulation Module***. The line graph option is also available for the history of EMG threshold values to monitor the patient muscle performance along the rehabilitation period. The screenshots of ***Database Module*** is depicted in Figure 3.11.

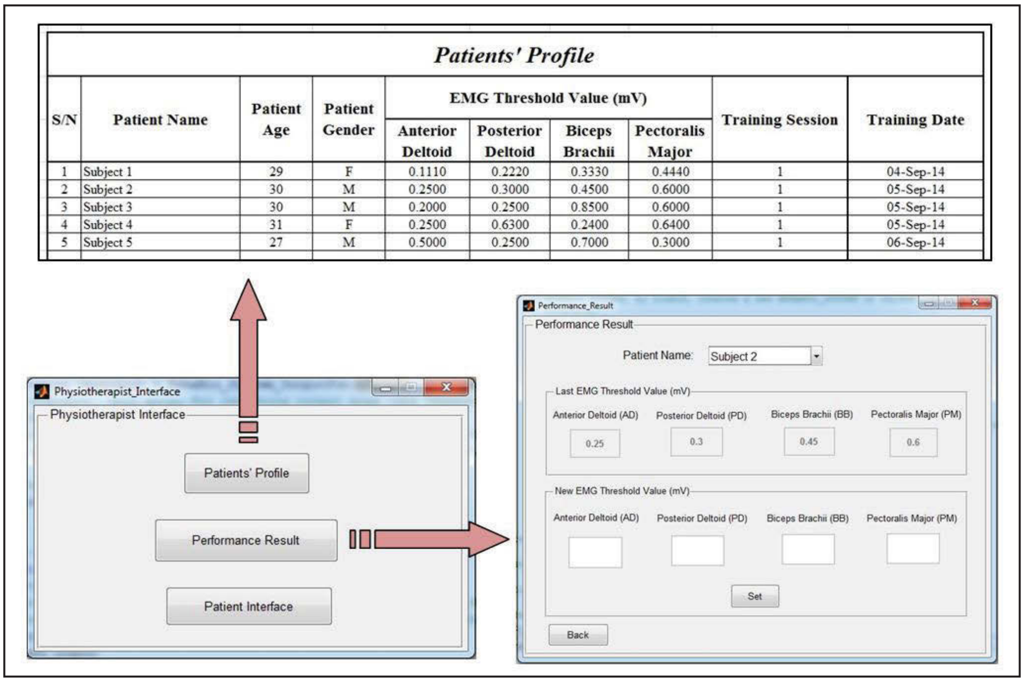


Figure 3-11: Database Module in RehaBio

3.5.2.2. Therapeutic Exercise Module

Therapeutic exercise module stores all the therapeutic exercises for upper limb rehabilitation. The exercises include Transfer Objects Rehabilitation (TOR), Circular Motion Rehabilitation (CMR), Feeding Animal Rehabilitation (FAR), Ping Pong Rehabilitation (PPR) and Balloon Collection Rehabilitation (BCR) as depicted in Figure 3.12. All the exercises are developed according to the serious game design theory which is presented in section 3.2.2. This module is able to be accessed by both physiotherapist or carer and patient. They are developed in Adobe Flash Professional platform where ActionScript API is utilised to create the AR environment, look for the suspected markers and detect collision between colour marker and virtual objects during the exercise. As AR is the combination of real world and virtual world, the virtual objects in this module will lay on top of the video image which is fed via webcam to create the AR environment. Detail development of individual exercise, rehabilitation purpose, relationship between traditional rehabilitation exercises and RehaBio therapeutic exercises, custom made Colour Tracking Algorithm and fast Collision Detection Algorithm will be discussed later in section 3.5.4.

3.5.2.3. Development of Biofeedback Simulation Module

Biofeedback simulation module provides real time muscle performance of the user while performing a specific rehabilitation exercise. This module employs FlexComp data acquisition system from Thought Technology to acquire the sEMG data in real time and then processes it in Matlab platform to integrate with developed rehabilitation exercises. The raw signal from the user is acquired by pre-amplified EMG MyoScan sensor

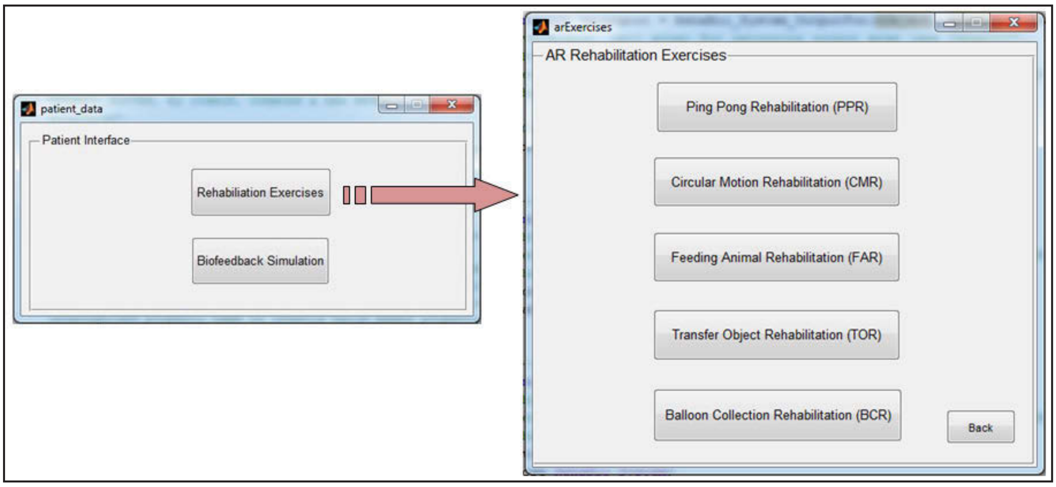


Figure 3-12: Augmented Reality based Rehabilitation Exercises in RehaBio

permitting input range of 0–2000 μV and channel bandwidth of 10 Hz to 1 kHz. The raw signal is first processed by band-pass filtering (20Hz - 500Hz) to remove both low and high frequency noise. The valuable features are then extracted from these signals with root mean square (RMS) based on the following equation:

$$EMG_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} sEMG(i)^2} \tag{1}$$

where *sEMG*(*i*) is the amplitude of the signal in *i*th sampling, *N* is the number of samples. The sampling rate of 2048 Hz was used in this work. Although there are many other feature extraction methods such as integrated absolute value (IAV), autoregressive (AR), zero crossing (ZC), etc., which are available, RMS method is employed as it provides good real-time information. The value of EMG_{rms} is then compared with predefined threshold value to activate the muscle animation as muscle contribution.

The locations of the EMG sensors are as depicted in Figure 3.13. Total of four sEMG signals are recorded from four upper limb muscles: AD, PD, BB and PM muscles, while performing the rehabilitation exercises. The choice of the muscles is based on the most contributing muscles while performing the developed exercises. This is achieved via experiment and details of such experimental results are discussed in section 3.5.5. In the context of software development for this module, it is made up of several sub-modules to read the live data of EMG, extract EMG features by RMS, display the real-time signals and perform the simulation of active muscles in real-time via Graphical User Interface (GUI). By controlling of "START" and "STOP" button in biofeedback simulation GUI, the user is able to manipulate the acquisition and termination of EMG signals for simulation. The individual sub-module of biofeedback simulation and its functions are explained as follows:

- ***Initialisation:*** This sub-module is responsible to initialise the activeX control in the figure window and initialize the Thought Technology encoder to be ready for live data collection.
- ***Setups:*** This module is in-charge of setting up the encoder and channels' properties; in this work one encoder and four channels are utilised.
- ***Live data:*** This module provides the collecting of all the four sEMG data live from specified muscles through Thought Technology Myoscan EMG sensors.
- ***Plot data:*** All the processed data will then live-tream and plot in real-time by this sub-module.

- ***Simulation:*** This is responsible for simulation of muscle by displaying the different colours for different muscles according to the EMG threshold value (amplitude). Different muscles have different threshold value and that value will be defined by the physiotherapist in charge. If the threshold value of a particular muscle is above the predefined values, that muscle's colour will change. This is an indication of that particular muscle contribution in a specific movement. The series of threshold values are stored in this sub-module and is able to be retrieved and evaluated by the physiotherapist in future. After evaluation of previous muscle performance through threshold values, the physiotherapist has to set the new value for current training session.
- ***Stop connections***: This module will release the handle to ActiveX objects and then stop the connection from all the channels and save all the collected sEMG data of muscles' performance.

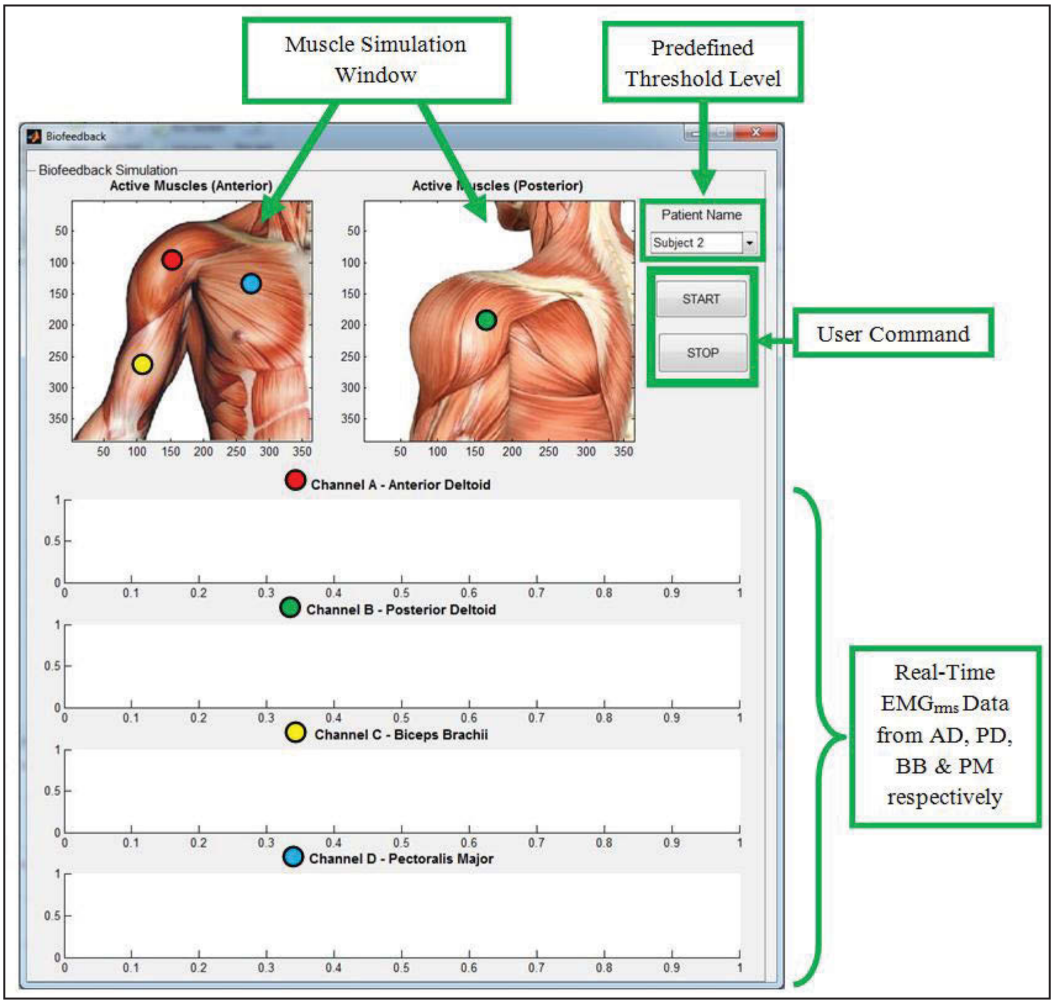


Figure 3-13: Biofeedback Simulation GUI with Electrode Sites

The screen shot of biofeedback simulation module is portrayed in Figure 3.13.

There are two muscle windows for biofeedback simulation and four line graphs representing Channel A: anterior deltoid, Channel B: posterior deltoid, Channel C: biceps brachii and Channel D: pectoralis major muscle signals. Four sEMG electrodes are attached to the muscles of interest in order to detect the EMG threshold level in real time for the activation of muscle simulation which will be displayed in two muscle windows. Simulation will activate when recorded sEMG signals are above the predefined threshold value. When the recorded sEMG signals are above predefined activation level, the muscle colour will change so that patient and therapist can observe the current active muscle during specific exercise movement. This module provides two-fold benefits in RehaBio system: one for patient motivation where patient is able to observe the performance of muscle contribution during performing the therapeutic exercise as immediate visual feedback and another benefit is the evaluation of muscle performance by physiotherapist just by tracking or plotting the history of sEMG data contributed throughout the training sessions. The overall steps of developed biofeedback simulation module are listed in the flowchart in Figure 3.14.

3.5.3. System Output

The output module of the system consists of computer monitor and speaker. The monitor is a device providing real-time view of the real-world environment that has been enhanced by adding virtual computer generated information to it. In other words, this is the place to perceive the visual feedback such as manipulation and action of the user in real-time through this monitor. In additional to that, audio feedback is also integrated in all exercises for user motivation.

3.5.4. Development of AR based Therapeutic Exercises

Therapeutic exercises are developed within the context of movement and mind-focused therapies. These developments had published in [8, 213, 214]. The basic principles of neural plasticity that govern learning in damaged brain are thoroughly considered for the developed exercises in RehaBio system. In order to meet the first two principles; ***Use it or lose it*** and ***Use it and improve it***, the therapeutic exercises must be motivated enough for the patients to engage in the exercises for long term training. As previously discussed in Chapter 2, Augmented Reality (AR) and in rehabilitation field and biofeedback provide

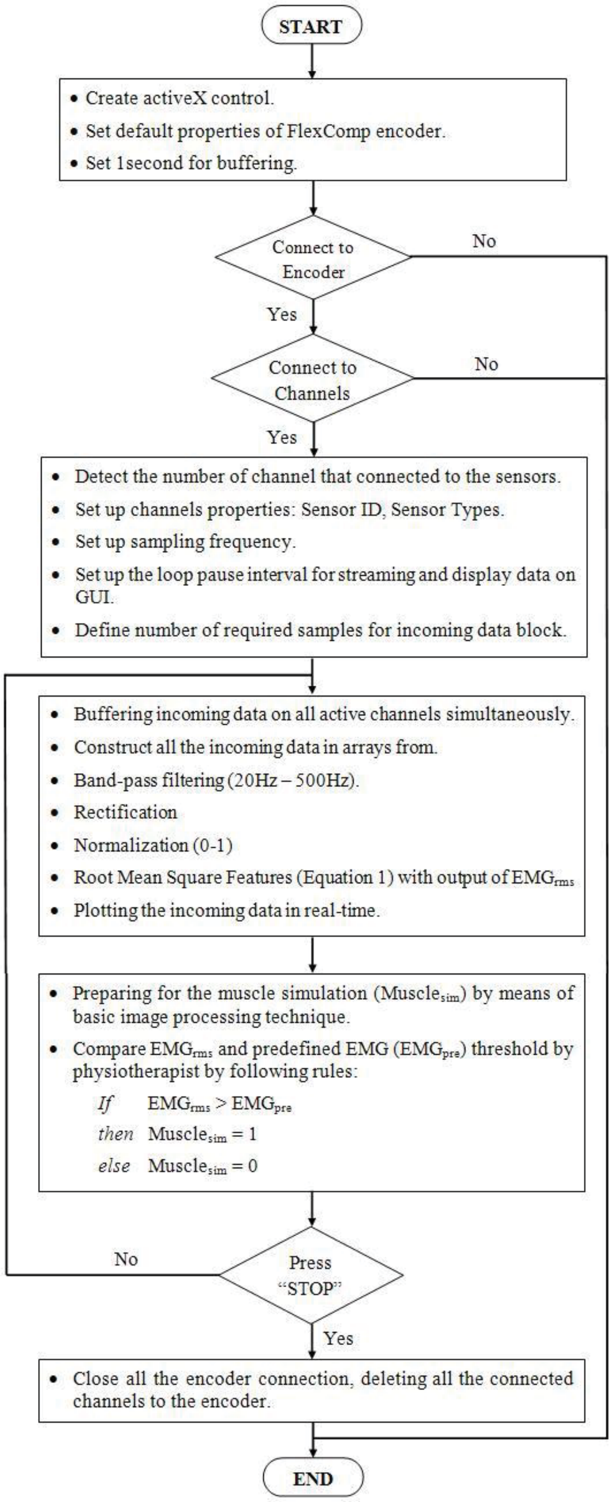


Figure 3-14: Flow Chart of Biofeedback Simulation Module

more benefit than conventional rehabilitation therapy; all the exercises in RehaBio system are developed in AR environment by augmenting the virtual objects on the real scene which provides better motivation with long term engagement and faster recovery. In addition to this, all the exercises are developed in an iterative approach in such a way that they are developed, tested and improved to achieve better game design theory, user-friendly interaction and meet the user requirements and expectations. This is to meet the neural plasticity principles of ***Specificity***, ***Time Matters***, ***Salience Matters***, ***and Age Matters*** to drive the fast recovery. In addition to this, the ***Intensity*** and ***Interference*** of the exercises must be considered properly so that the developed exercises can affect the induction of neural plasticity. Therefore, the exercise attributes are properly considered to suit all stage of paralysed patients and to induce the best eye-hand coordination therapy in motivating way and this detailed in the following section.

3.5.4.1. Therapeutic Exercise Attributes

Game attributes is one of the important factors to consider during game development especially for rehabilitation purpose. These attributes consist of motivation, type of motion and cognitive challenge. The important aspect of the motivation is the availability of opportunities of treatment and re-training in the longer term. The type of motion in rehabilitation therapy can either be focused on a simple motion with single muscle contraction or coordinated motion with multiple muscle contractions. In terms of cognitive challenge in rehabilitation exercise, it can be a very simple game design to understand and play easily in starting point and then slowly increase the difficulty level to enhance the recovery after some period of rehabilitation time. This is to induce the ***Transference*** principle to promote in induction of neural plasticity. In addition to this, all the therapeutic exercise can be played repetitively without losing the interest which is one of the important principles for neural plasticity. The concept of developed therapeutic exercise attributes is depicted in Figure 3.15.

From Figure 3.15, it can be clearly seen the overall motivation pathway with type of motions and level of cognitive challenge for each therapeutic exercise in RehaBio system. The lower left corner represents the movement of the exercise with basic motion and easy recognition while the top right corner represents the exercise which required random movement of arm via advanced recognition. Basic motion in RehaBio is defined as only 1 Degree of Freedom (DOF) being required to perform the exercise whereas random motion is made up of several DOFs to complete the exercise. The types of upper limb movement in RehaBio exercises are developed according to the HOPE: The Stroke Recovery Guide by National STROKE Association [193]. The clinical guidelines of HOPE and corresponding exercises in RehaBio system are tabulated in Table 3.1. In addition to the guidelines, RehaBio exercises are developed with customizable movement types, different

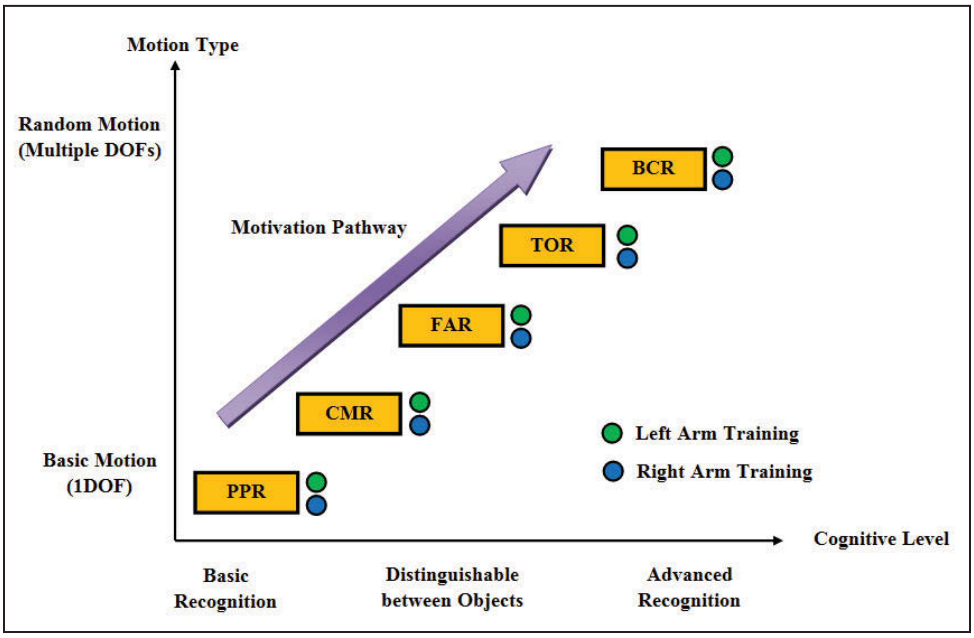


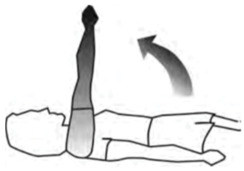
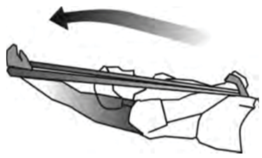
Figure 3-15: Therapeutic Game Attribute in RehaBio System

level of challenges with motivational biofeedback. The detailed developments of individual therapeutic exercise are explained in the following section.

3.5.4.2. Game Design for Ping-Pong Rehabilitation (PPR)

The PPR exercise is designed to maintain the bouncing ball within the display screen by moving the player's arm 'up' and 'down' as shown in Figure 3.16. The idea of the exercise is adopted based on the clinical exercise 1 from both mildly and moderately effected by the stroke stated in Table 3.1. It requires 1 DOF of movement at shoulder joint with simple recognition to complete the exercise. However, player requires playing against the computer with either affected left or right arm. In PPR exercise, the ball moves within the display screen with upper and lower boundary of the monitor. One side of the display screen border is limited by moving a block which is controlled by computer system according to the ball movement direction to restrict the ball from moving out of the display. The other side of the stage is to be controlled by the player arm where the colour marker is attached at the player's thumb to prevent the ball from moving out of the display. If the ball is successfully hit by marker, user will earn the score and be provided with the audio and visual feedback. When the score reaches to certain value, the speed of the ball will increase and move to the next level to increase the challenge and motivation. In every level change, the system will provide a warning message as a visual feedback for the player. The performance of the player is evaluated by comparing the overall score within

Table 3.1: Clinical Exercises vs. RehaBio Exercises

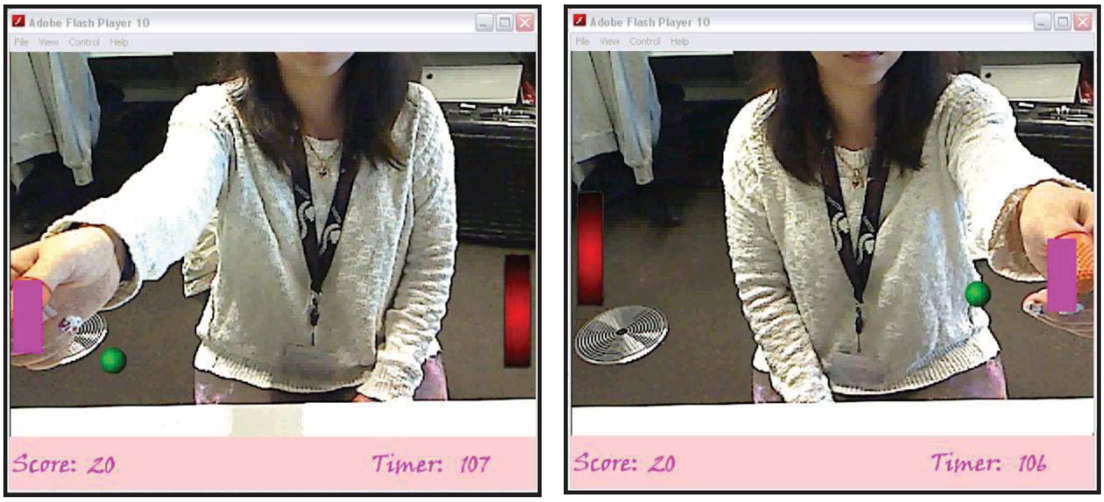
For mildly affected by stroke	
Exercise 1: To strengthen the muscles that stabilize the shoulder	
	
Clinical Exercise	***Corresponding RehaBio Exercise***
Shoulder Flexion Exercise	Ping Pong Rehabilitation (PPR)
Exercise 2: To strengthen the shoulder muscles as well as those which straighten the elbow	
	
Clinical Exercise	***Corresponding RehaBio Exercise***
Shoulder Diagonal Flexion Exercise	Transfer Object Rehabilitation (TOR) Circular Motion Rehabilitation (CMR)
Exercise 3: To strengthen the muscles which straighten the elbow	
	
Clinical Exercise	***Corresponding RehaBio Exercise***
Elbow Flexion Exercise	Balloon Collection Rehabilitation (BCR) Feeding Animal Rehabilitation (FAR)

For moderately affected by stroke	
Exercise 1: To enhance shoulder motion and possibly prevent shoulder pain	
	
Clinical Exercise	***Corresponding RehaBio Exercise***
Bilateral Shoulder Flexion (upto 90°)	Ping Pong Rehabilitation (PPR)
Exercise 2: To maintain shoulder motion	
	
Clinical Exercise	***Corresponding RehaBio Exercise***
Shoulder Diagonal Flexion (Horizontal Adduction) Exercise	Transfer Object Rehabilitation (TOR) Balloon Collection Rehabilitation (BCR) Feeding Animal Rehabilitation (FAR)

the given time among the therapy sessions. By performing of PPR exercise, shoulder flexion and extension movements will be induced by contracting of Anterior Deltoid (AD), Posterior Deltoid (PD), Biceps Brachii (BB) and Pectoralis Major (PM) muscles. In this way, player's eye-hand coordination will be trained and will increase the user visual motor skill.

3.5.4.3. Game Design for Circular Motion Rehabilitation (CMR)

The aim of the CMR is to collect the virtual objects from the same location and place them on respective transparent virtual objects that are indicated by an animated arrow along the semicircle trajectory as portrayed in Figure 3.17. The player needs to be able to recognize the different objects to be placed at the predefined location. The CMR exercise requires basic motion with 1 DOF in shoulder abduction and adduction motion and can be played by either left or right arm. It is developed based on the concept of clinical exercise 2 in Table 3.1 for both mildly and moderately paralysed patients. However, CMR integrates



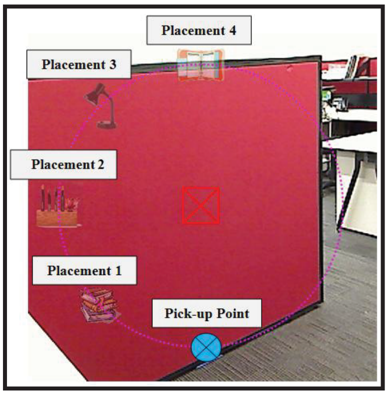
(a) Left Arm Training (b) Right Arm Training

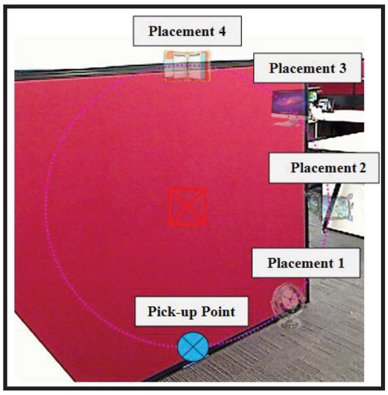
Figure 3-16: Ping Pong Rehabilitation Exercise

with additional features such as auto level increments that become wider degree in shoulder abduction and adduction angle to engage the player in exercise for the long term with immediate feedback to make the player action discernable. In the exercise, there are a total of four virtual objects that user requires to pick and place at the respective positions. Collision detection algorithm defines the pick and place and also increases the scoring engine for successful pick and place actions with audio and visual feedbacks. By performing CMR exercise the player's arm will achieve a wider range of motion in shoulder abduction and adduction and their associated muscles will strengthen.

3.5.4.4. Game Design for Feeding Animal Rehabilitation (FAR)

FAR is the exercise that a player requires to recognize between pick and place locations based on the indicators. To perform the arm movement in FAR, it requires a combination of multiple DOFs at the shoulder joint which resemble the arm movement of clinical exercise 2 from Table 3.1 but wider in joint angle at shoulder joint. The objective of the FAR exercise is to pick up the food and place it in the located food plate. The pickup position is indicated by an animated red arrow and the placed in the food plate position is indicated with a green arrow. Therefore player is expected to distinguishable between pick and place positions as well as being required to organize self path planning for arm movement. The player is required to finish placing all the food into the plate within a defined time. Upon successful placement player will be awarded by scoring up and immediate feedbacks. The outcome of the score will evaluate the performance of the player throughout the training sessions. The different height and width of the location of pick and





(a) Left Arm Training (b) Right Arm Training

Figure 3-17: Circular Motion Rehabilitation Exercise

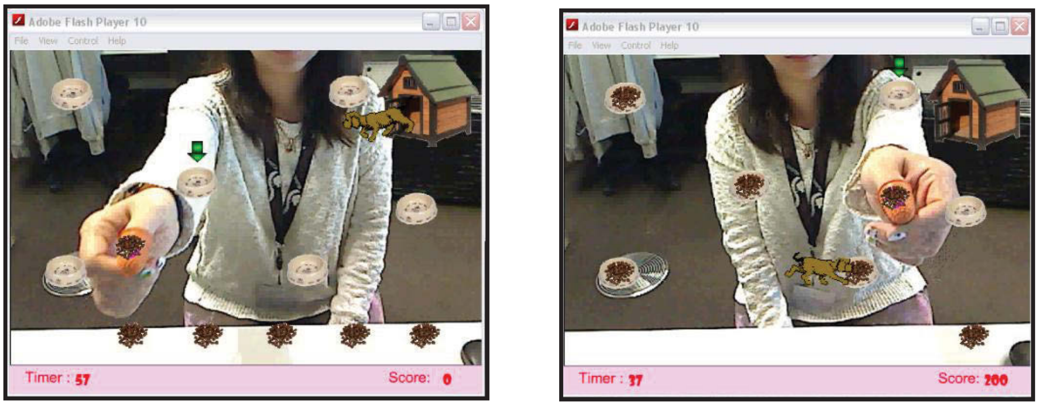
place will train the shoulder movement in 2 DOFs: shoulder flexion, shoulder extension, shoulder abduction and shoulder adduction by contracting the associated muscles. The FAR exercise is displayed in Figure 3.18.

3.5.4.5. Game Design for Transfer Object Rehabilitation (TOR)

TOR exercise requires advanced recognition with multiple DOFs of arm movement to perform the exercise by following the indicated trajectories. There are five different solid virtual objects which are located at the bottom row of the screen. At the top row of the screen, the same shape but hollow virtual objects are located in different order. The object that player requires to pick will be displayed as a blinking object and to be placed at the correct hollow shape as depicted in Figure 3.19. The successful placement will be awarded by scoring system and there won't be any misplacement done by the player as this is the misplacement free exercise. However, player has to play against the timer and within the given time player has to complete all the placements to earn the highest score. The performance of the player will be evaluated by the score achieved during training sessions. By collecting and placing the virtual objects in TOR exercise, shoulder abduction, adduction motion and minimum contribution of shoulder flexion and extension motion is achieved. Like in other exercises, immediate audio and visual feedbacks are integrated for motivation and long term engagement purposes.

3.5.4.6. Game Design for Balloon Collection Rehabilitation (BCR)

The aim of BCR exercise is to catch the dropping balloon at a time with colour marker that is attached to the player's thumb and place it into the box which is located at the centre of the screen as depicted in Figure 3.20. This game is designed to spawn the balloons randomly and therefore, player is expected to move his/her arm in various directions to



(a) Left Arm Training (b) Right Arm Training

Figure 3-18: Feeding Animal Rehabilitation Exercise

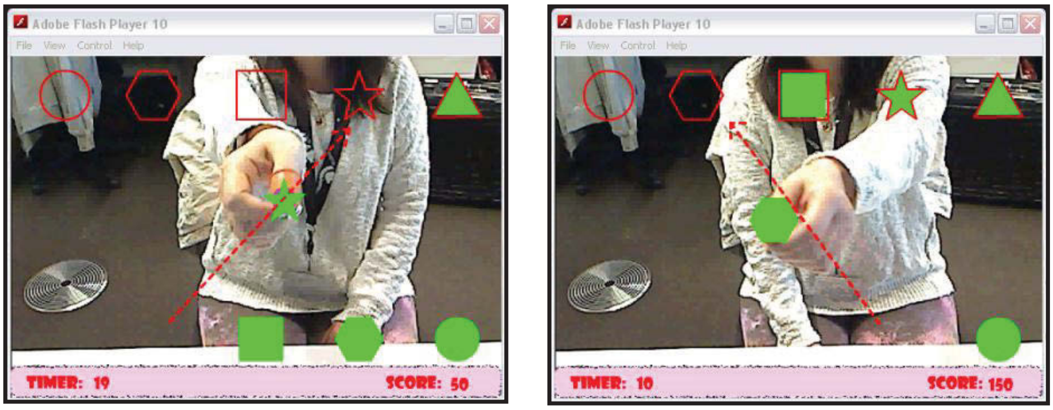
catch the dropping balloon. There are two types of colour balloons available. The player requires to choose only one colour (either pink or green) and place it into the box. This is to induce the player's ability to distinguish among the falling balloons. Correct selection will be rewarded by increasing the score with applause feedbacks. There is no penalty for wrong picking but a warning message will be displayed to the player as a reminder for future selection. When the score reaches a certain value, the speed of the balloon falling will be increased automatically and transfer to the next level which will be indicated with message box. In this way, player's muscles will become stronger unknowingly over the period of time. By performing BCR exercise, a wide range of motions at shoulder joint such as flexion, extension, abduction, adduction and some motion at elbow joint such as flexion and extension will be achieved and the associated muscles will strengthen.

3.5.4.7. Colour Tracking Algorithm

In RehaBio system, a single webcam is utilized as a tracking device to track the colour marker which is worn by the user. As discussed in section 3.4.1, there are several methods to develop the object tracking algorithm according to the application. In the development of RehaBio system, the object of interest is tracked based on colour feature selection method. The algorithm of chosen method is proposed in Figure 3.21 flowchart:

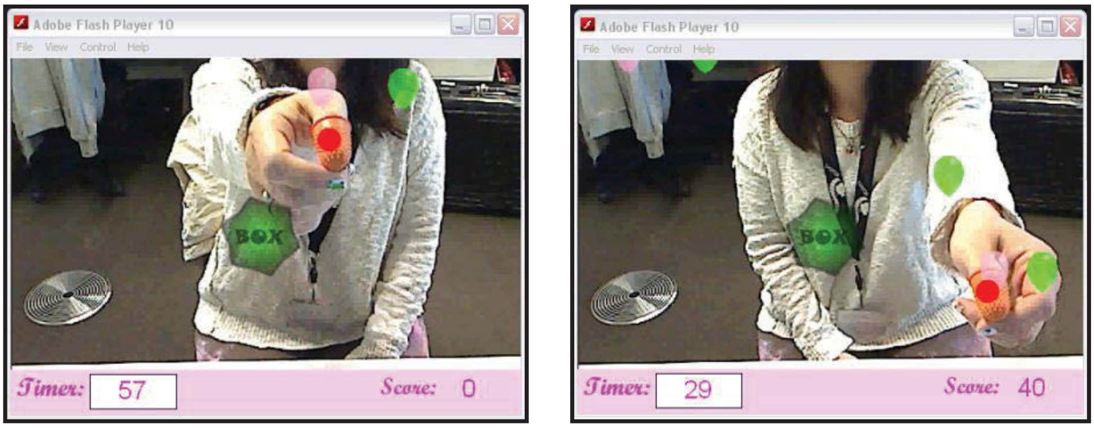
1. Initialization:

    - Choose the colour of interest in terms of pixel on the display screen by clicking the mouse (input device) on the colour marker.



(a) Left Arm Training (b) Right Arm Training

Figure 3-19: Transfer Object Rehabilitation Exercise



(a) Left Arm Training (b) Right Arm Training

Figure 3-20: Balloon Collection Rehabilitation Exercise

- Detect input/output device colour model for RehaBio system for best tracking result. Most of the display screen such as computer monitor, projector are built in with Red (R), Green (G), Blue (B) colour space for their best display. RGB colour space also has the advantage of being less sensitive to noise [215] and that is why it is very useful in tracking applications.

2. Once colour model, RGB colour space, is detected, the algorithm starts finding the red, green and blue components of the colour of interest.

3. The 24 bit RGB values are assigned into respective variables to create a byte array as in the following manner where Red sample in the highest 8 bits, followed by the Green sample and Blue sample in the lowest 8 bits as shown in Figure 3.22.

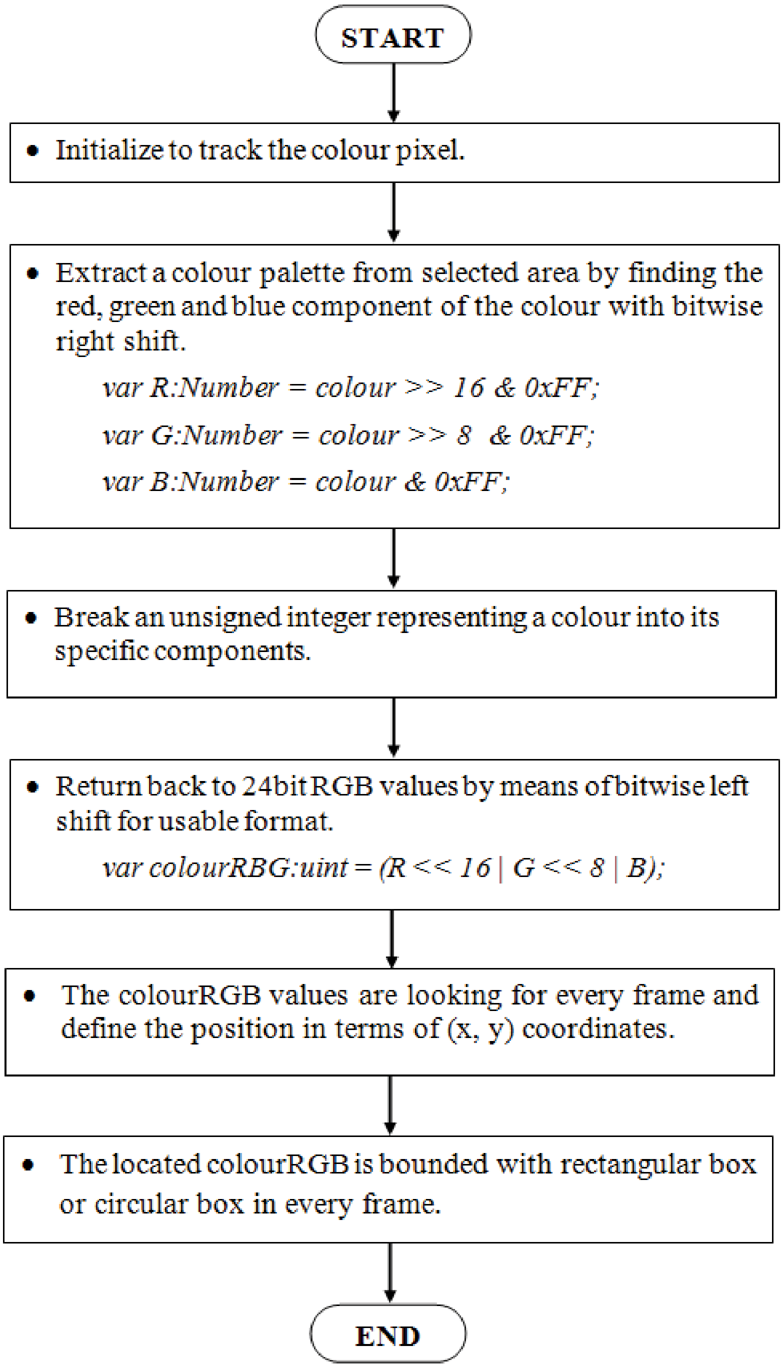


Figure 3-21: Flowchart of the proposed *Colour Tracking Algorithm*

4. User chosen pixel from webcam feed image will convert into RGB values from 24 bit hexadecimal by moving the bits to the right by a certain amount with bitwise right shift.

Sample Length	8								8								8							
Channel																								
Bit Number	23	22	21	20	19	18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0

Figure 3-22: Arrangement of Red-Green-Blue Values in RehaBio system

5. Return back the selected RGB values as a new byte array with bitwise left shift operator. This new byte array will be continuously finding in every incoming frame as tracking the select pixel.

6. The rectangular region that fully encloses all pixels of a specified colour within the webcam fed image will be created.

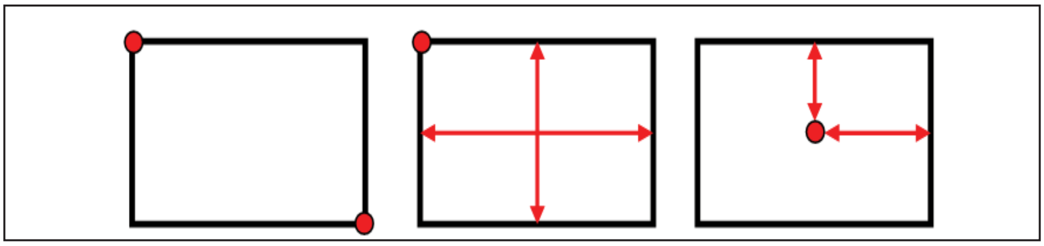
7. This rectangular region will represent either rectangular or circle virtual object for post processing such as detection of collision or manipulation.

3.5.4.8. Collision Detection Algorithm

As aforementioned in section 3.4.4.2, the development of collision detection algorithm should be based on the following factors: *application domain representation*, *different types of queries*, *environment simulation parameters*, *performance*, *robustness* and *ease of manipulation and us*e. In RehaBio system, with thorough consideration with above mentioned factors, custom built Collision Detection Algorithm is proposed as follows.

Application domain representation: In RehaBio system, the representation of the domain is based on AABB method due to its inexpensive computation and faster test. There are three common types of AABB representations: (1) min-max (2) min-widths, and (3) center-radius as shown in Figure 3.23.

First representation type specifies the bounding region of the object and is based on the two opposite corner points: minimum and maximum coordinate values along each axis. The second type defines the bounding volume of the object and is based on minimum corner point and the width or diameter extents dx, dy, and dz from this corner. The last representation type defines the AABB as a center point C and halfwidth extents or radii rx, ry, and rz along its axes. Among these three types of representations, the virtual objects in RehaBio employ center-radius types due to it being the most efficient in storage requirement as halfwidth values are able to be stored in fewer bits than other types of representation methods. Although there are several collision cases available, the test



(a) (b) (c)

Figure 3-23: Common types of Axis Aligned Bounding Box representations

between AABBs (AABB-AABB intersection) has been chosen due to its fast detection and less memory usage. Overlapping test between AABBs in RehaBio follows the rules based on the algorithm 3.1 and the example of AABB test in Balloon Collection Rehabilitation is portrayed in Figure 3.24.

Types of Queries: After defining the representation and checking for rough collision detection, it is necessary to find the penetrating depth to proceed to the action. This is where types of queries come into the picture. In RehaBio exercises, approximation queries are employed under intersection testing for its fast and easy implementation. After the bodies have checked based on the algorithm 3.2, penetration depth is computed by finding the shortest movement vector that would separate the objects. When that movement vector is less than given tolerance, the bodies are intersecting. Below is the algorithm to define the approximation queries in developed exercises.

Environment Simulation Parameters: To speed up the detection process in RehaBio exercises, broad phase is conducted to separate into smaller groups of objects that have the potential to collide and remove those that definitely are not colliding. Total numbers of bodies that are required to be checked for collision detection in PPR exercise are 3, CMR exercise are 6, FAR exercise are 13, TOR exercise are 11 and BCR exercise are 4.

Performance, Robustness, and Ease of manipulation and use: The results of these factors are mainly and directly reflected from the above decision and choice of representation, type of queries, optimization and the simulation parameters.

3.5.5. Experiments and Results

There are three phases of experiments with RehaBio system and the results had been published in [92, 115, 216]. The first phase is carried out to verify the significant

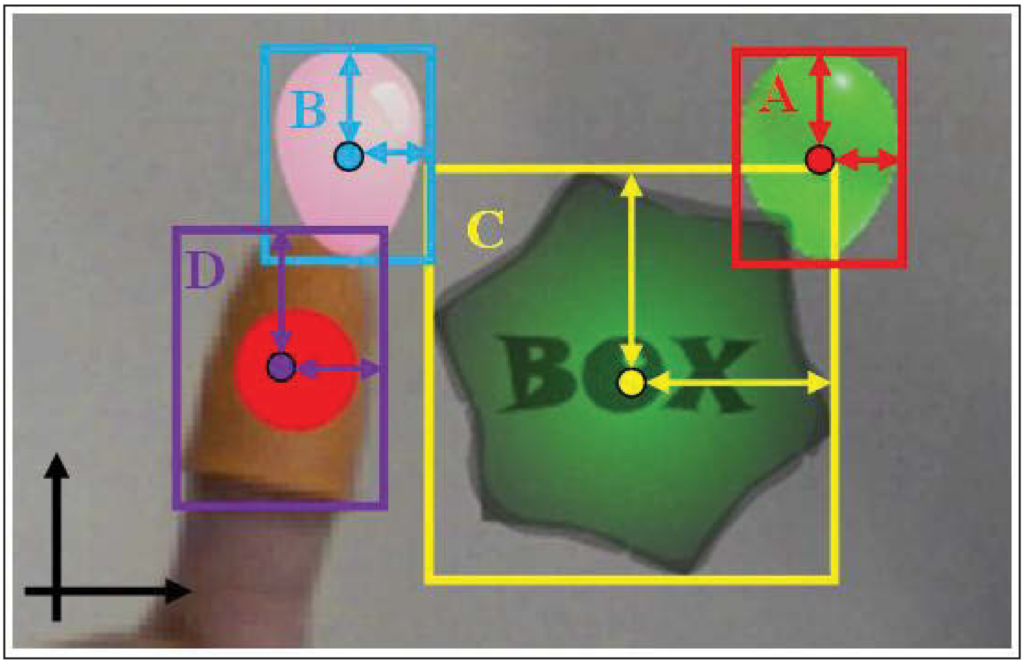


Figure 3-24: Axis Aligned Bounding Boxes in Balloon Collection Rehabilitation

contribution of the muscles for every articulation in shoulder and elbow joint followed by the muscle contribution in each exercise which had been published in [217]. The second phase of the experiment is to determine the effectiveness of developed therapeutic exercises in RehaBio system. These results had been published in [216, 218]. The final phase of the experiment is to conduct the efficacy of complete RehaBio system where it integrates with database module, therapeutic exercise module and biofeedback simulation module.

3.5.5.1. Participants

In all phases, ten participants with normal eyesight and sense of touch were recruited to participate in all the experiments. All of the participants were students from the University of Technology Sydney and all participants signed an informed consent document. Among them, nine of the participants were right handed and one of them were left handed.

3.5.5.2. Setting and Apparatus

Before starting the experiment, hardware set up was performed. Desktop personal computer (PC) (Windows 7, 64 bit, Intel Core i5, 2.70 GHz, 64 GB of memory), webcam and FlexComp EMG data acquisition device from Thought Technology were utilised in all experiments. Four MyoScan sensors from Thought Technology were connected to four channels of FlexComp Infiniti encoder. The encoder was then connected to TT-USB interface unit via fibre-optic cable and the interface connected to a USB port of the computer. Four MyoScan sensors were attached to the four upper limb muscles. Before the sensors were attached, proper skin preparation was performed to receive a good signal and minimize the artefacts. The skin was cleaned by applying the alcohol wipe and letting it dry for a few seconds and then sensors were attached as depicted in Figure 3.13. The raw sEMG signals from anterior deltoid, posterior deltoid, biceps brachii and pectoralis major muscle were recorded via channel A, channel B, channel C and channel D of FlexComp Infiniti encoder, respectively.

3.5.5.3. Experiment 1: Analysis of Muscles Contribution during Shoulder Articulation

As first phase of experiment, the contributions of the muscles based on types of movement were analysed. During the experiment 1, all the participants or subjects were requested to perform four types of arm movements: 1) shoulder flexion and extension, 2) shoulder abduction and adduction, 3) elbow flexion and extension, and finally 4) shoulder flexion followed by shoulder abduction, adduction and then shoulder extension which were required to perform in RehaBio exercises. Each subject was requested to perform each movement for 10 trials with resting time of 10 seconds in each trial. During data collection, all the participants were requested to move their upper limb with a constant speed as much as possible so that the data will be consistent and able to be analysed easily. The raw EMG data was recorded at 2048 sampling rate and was band-pass filtered with cut-off frequencies of 20 and 500Hz to minimize noise owing to motion artefacts and the EMG amplifier. The filtered EMG was used to extract the important features with Root Mean Square (RMS) method to analyse the muscle performance and contribution during the specific movement.

The processed data are portrayed in Figure 3.25 to Figure 3.28 according to the type of movement. The figures illustrate each muscle performance in each type of movement of 10 trials with their sEMG value (also known as threshold level or activation level). The grey shaded areas represent the quantile of the EMG distribution across 10 trials. This analysis is important as muscle activation level or threshold value of each contracted muscle is able to be determined from these figures in which this threshold value will be used to control for biofeedback simulation in RehaBio system. Figure 3.29 represents the most contributed muscles in specific type of movement across 10 trials from 10 random subjects. From all trials, it was observed that muscle performances are quite consistence except some

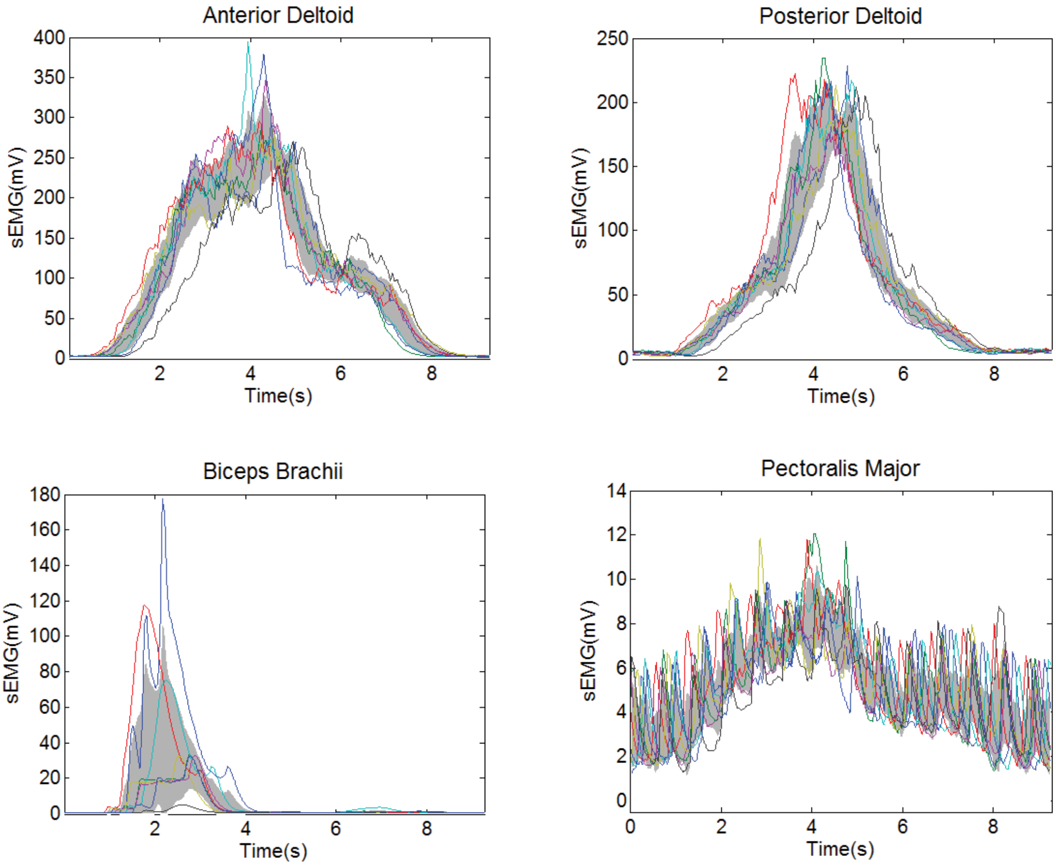


Figure 3-25: The performances of 4 shoulder muscles during shoulder flexion-extension articulation from one subject. The grey areas represent the 0.68 quantile (i.e. mean+s.d.) of the EMG distribution.

variation in sEMG activation value. Although all the muscles from the upper limb are involved in upper limb articulation, in this experiment, four major muscles performance are analysed for four types of movements: shoulder flexion-extension motion, shoulder abduction-adduction, elbow flexion-extension and shoulder flexion-adduction-abduction-extension motion.

During shoulder flexion-extension motion, anterior deltoid, posterior deltoid and biceps brachii muscles are contracted more than the rest of the muscles for all subjects. This indicates that performing of shoulder flexion-extension motion will increase the strength of anterior deltoid and posterior muscles mostly. During shoulder abduction-adduction motion, it was found that anterior deltoid, posterior deltoid and biceps brachii muscles were contracted and pectoralis major muscle were almost at resting value. Although anterior and posterior deltoid muscles were contracted the most in both movements, in most of the trials, the activation value of both muscles was higher in shoulder flexion-

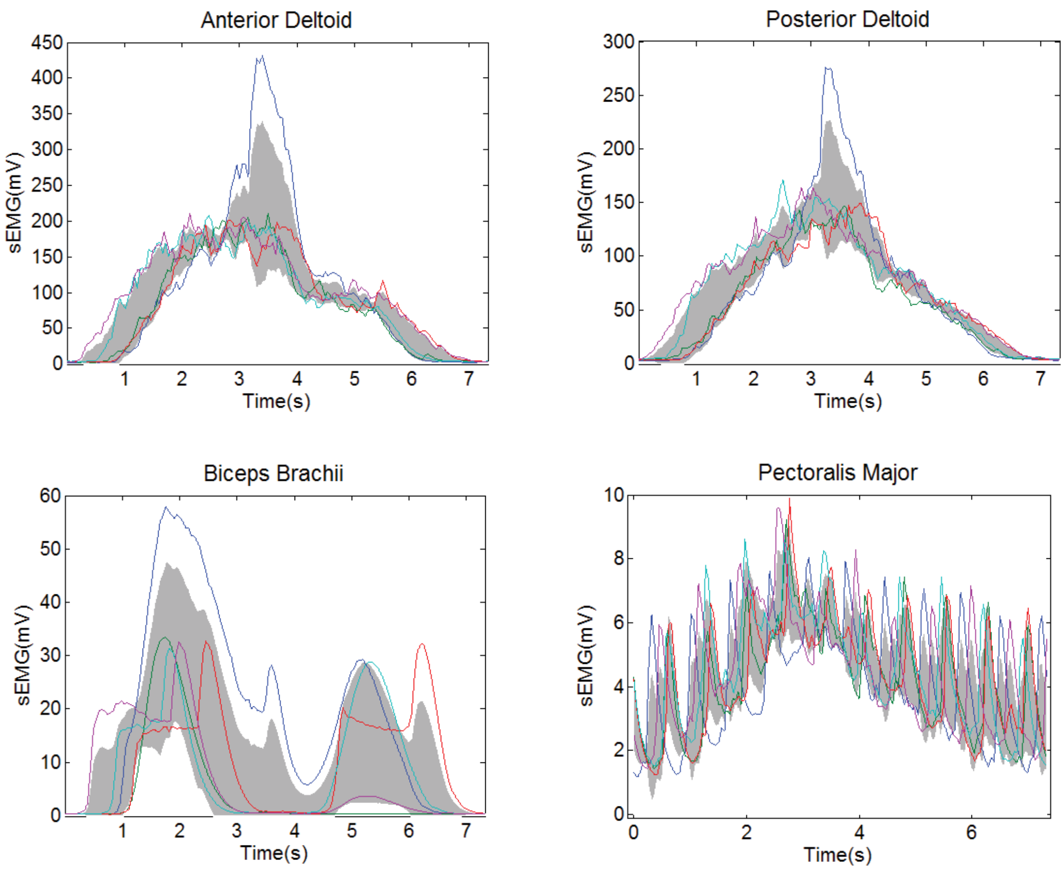


Figure 3-26: The performances of 4 shoulder muscles during shoulder abduction-adduction articulation from one subject. The grey areas represent the 0.68 quantile (i.e. mean+s.d.) of the EMG distribution.

extension movement. During elbow flexion-extension movement, anterior deltoid, posterior deltoid and pectoralis major muscles were almost at resting point and only biceps brachii was contracted the most. Therefore, the activation of biceps brachii muscle is highly related for elbow flexion-extension motion. The last motion, shoulder flexion-adduction-abduction-extension was attained due to all muscles: anterior deltoid, posterior deltoid and biceps brachii muscles and pectoralis major, contracted. Among these muscles, pectoralis major was significantly contracted. Therefore, to summarise the relationship between motion and muscle contribution, anterior and posterior deltoid muscles are trained during shoulder flexion-extension motion while elbow flexion-extension motions train biceps brachii muscles. The last motion will train and strengthen the anterior deltoid, posterior deltoid, minimum effect of biceps brachii and finally pectoralis major muscles.

3.5.5.4. Experiment 2: Therapeutic Rehabilitation Exercises

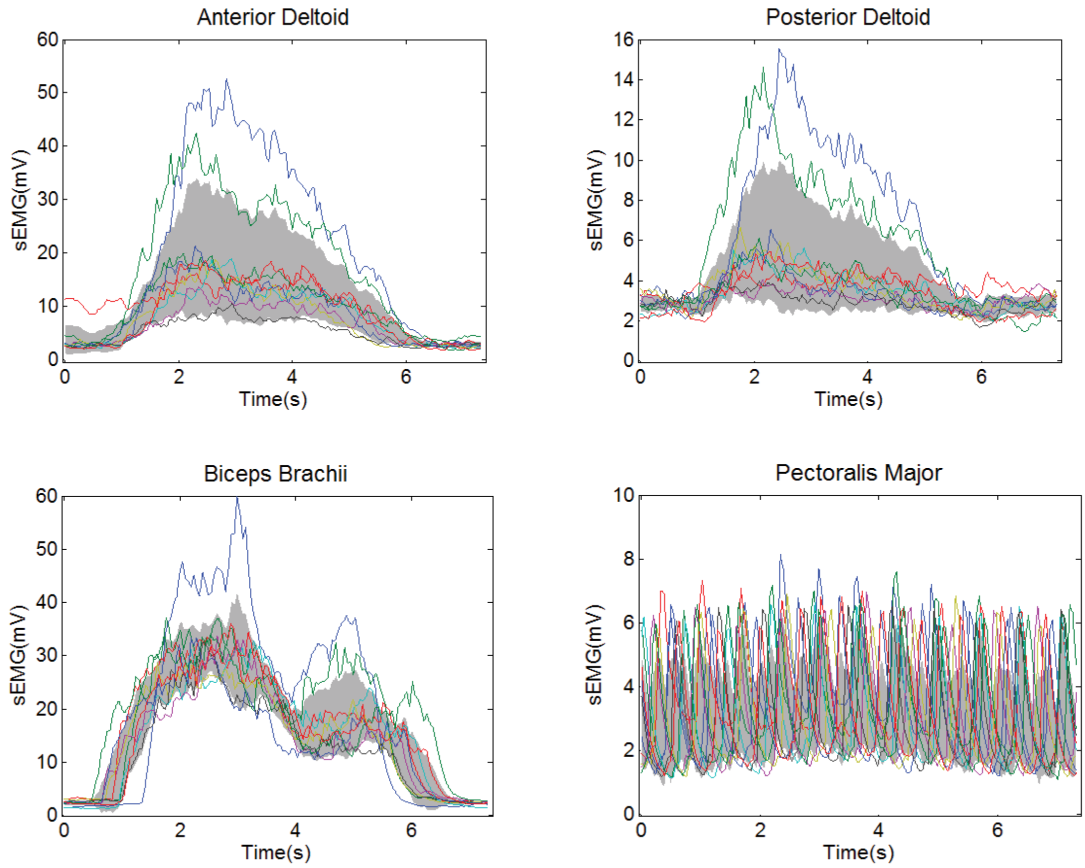


Figure 3-27: The performances of 4 shoulder muscles during elbow flexion-extension articulation from one subject. The grey areas represent the 0.68 quantile (i.e. mean+s.d.) of the EMG distribution.

In the second phase of experiment, all the participants were requested to perform therapeutic exercises: PPR, CMR, FAR, TOR, and BCR. The procedures to follow all the rehabilitation exercises are as follows:

- Physiotherapist, carer or player is expected to choose the appropriate rehabilitation exercise from AR rehabilitation exercises GUI.
- Subsequently, the intro page of the exercise will display and 'How to Play' instruction will present to the user for easy understanding.
- For some exercise, the duration of the exercise is expected to be defined by physiotherapist or carer or player before the game play.
- Choose either left or right arm to be trained.
- After choosing left or right arm exercise, the system will ask for the permission to access the webcam to prepare the AR environment.

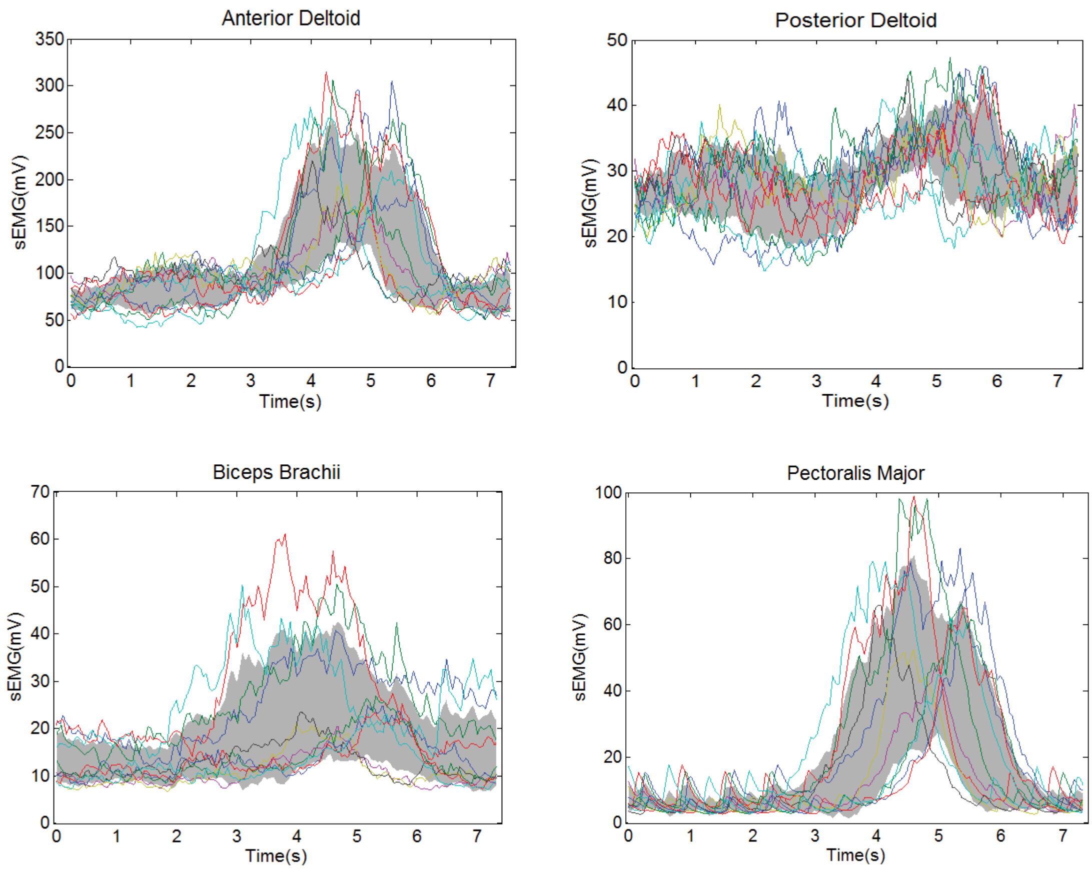


Figure 3-28: The performances of 4 shoulder muscles during shoulder flexion followed by abduction-adduction and then shoulder extension articulation from one subject. The grey areas represent the 0.68 quantile (i.e. mean+s.d.) of the EMG distribution.

- Once access to the webcam is granted, the webcam will feed the video image on the display screen and the instruction ‘Please Click on the Marker’ will be displayed on top of that video image.
- When the user clicks on the colour marker which is worn by the user’s thumb, five seconds of countdown timer will start. This countdown will allow the user to be ready to start the rehabilitation exercise.
- When five seconds timer is up, the chosen rehabilitation exercise will display and the patient will need to start the rehabilitation exercise.
- Once the exercise is started, the second timer will start counting down the duration of the training (in some cases, this is defined by the user). At the same time immediate visual and audio feedback will be provided according to the performance of the player.

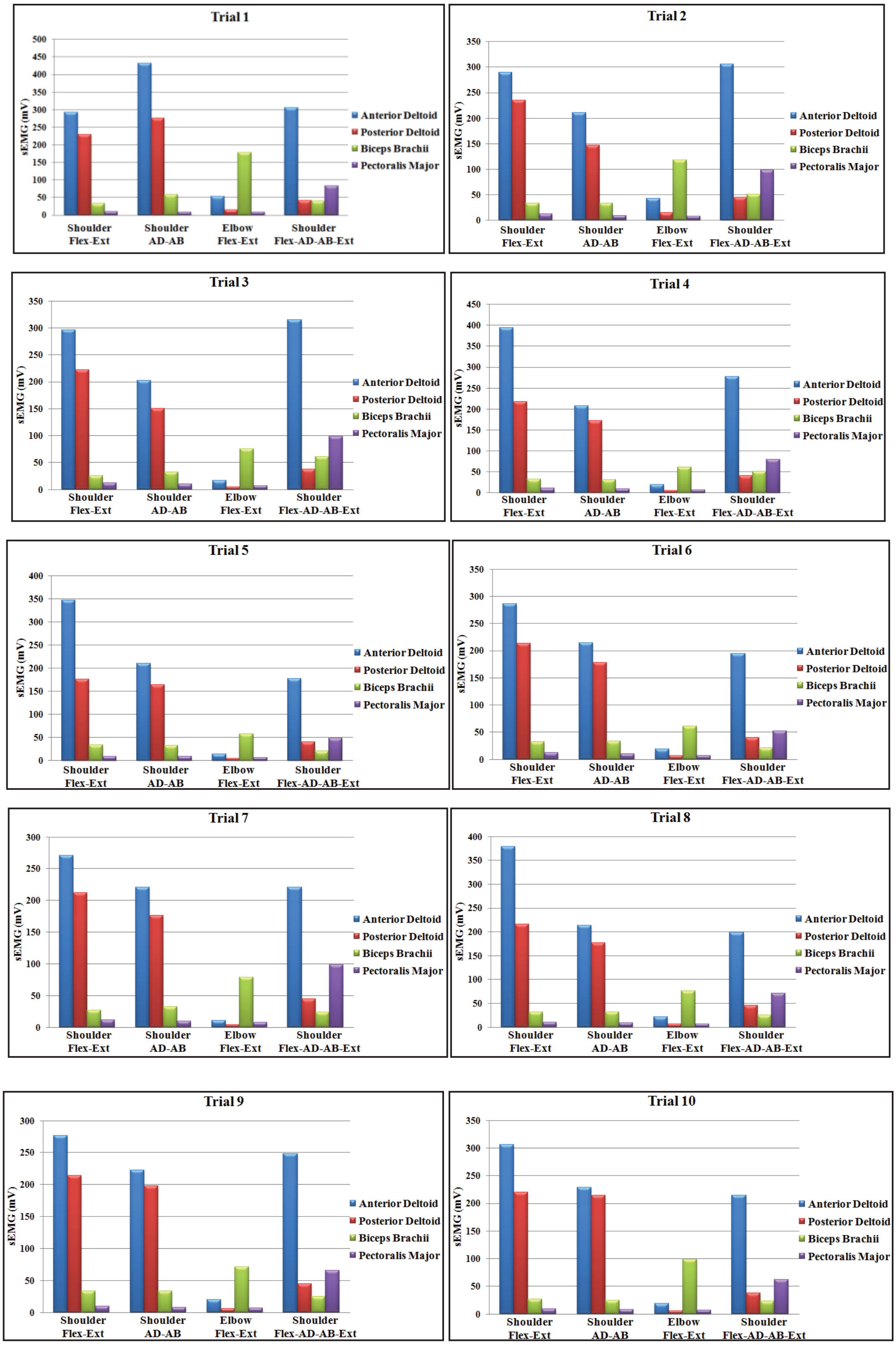


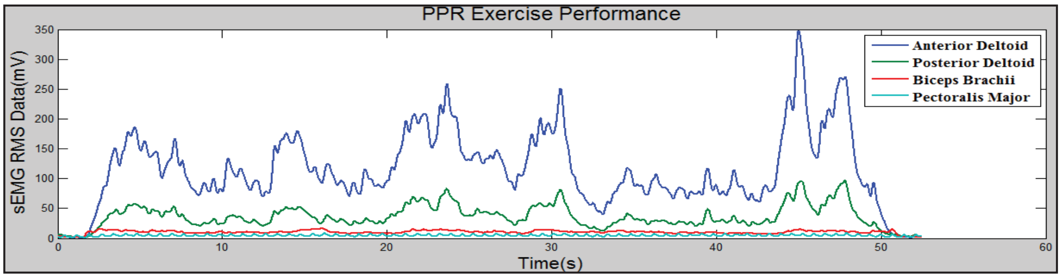
Figure 3-29: Muscle contributions in respective upper limb movement across 10 trials from 10 subjects

- When the second timer is up, the summary page will display with 'time's up' notification and total score of the user achievement.

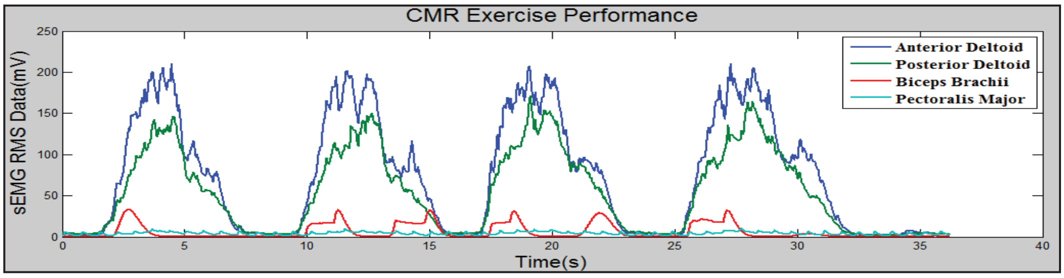
After completion of the exercise, the important data such as threshold level, trajectory performance, score, and exercise duration are saved in the database for physiotherapists to analyse the player's performance. There are three types of analysis which have been performed in this experiment 2 namely 1) ***Data Analysis*** where the muscle contribution are analysed during each exercise, 2) ***Performance Analysis*** where arm trajectories are recorded and analysed, and 3) ***Questionnaire*** for each therapeutic exercise.

In ***Data Analysis***, the muscle performance in each exercise is analysed. After analysing muscle performance by all the subjects in this experiment 2, the similar pattern of the EMG signals are found with minimum variation in activation values as sEMG contributions of individuals are different from one another. The examples of muscle performance in each exercise are illustrated in Figure 3.30. During PPR exercise, the subject only needs to move in shoulder flexion-extension movement and therefore, his anterior and posterior deltoid movements contribute the most with the minimum contribution of biceps brachii muscle as shown in Figure 3.30(a). The muscles' performance of CMR exercise is also very similar to that of PPR exercise with difference in sEMG activation level as anterior and posterior deltoid muscles are the main contributors for shoulder abduction-adduction motion as shown in Figure 3.30(b). Therefore, performing PPR and CMR will help to strengthen the anterior and posterior muscle as well as to achieve a wider range of motion in shoulder flexion, extension, adduction and abduction motion. In FAR and BCR exercises, all the muscles are contracted during the whole exercise duration as shown in Figure 3.30 (c) and (d). This indicates that to perform FAR and BCR exercises, anterior deltoid, posterior deltoid, biceps brachii and pectoralis muscles are required to contract during the exercise. Therefore, both exercises provide a wide range of movements in shoulder flexion-adduction-abduction-extension and strengthen all the studied muscles. During TOR exercise, anterior and posterior deltoid muscles are most contracted due to shoulder diagonal flexion and extension movement as illustrated in Figure 3.30 (e). Hence, TOR will train for the wider range of shoulder articulation with stronger associated muscle activities.

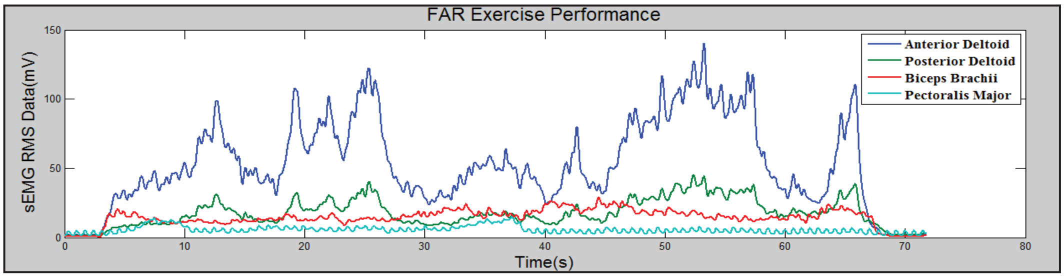
After ***Data Analysis*** has been performed, the ***Performance Analysis*** is conducted to analyse the player performance. This is necessary as EMG data alone cannot assess the performance of the player. The EMG data are one of the indications in muscle contribution of the particular exercise, determining the threshold level at the time of training period and giving indication of muscle fatigue. The actual performance is still based on the trajectory



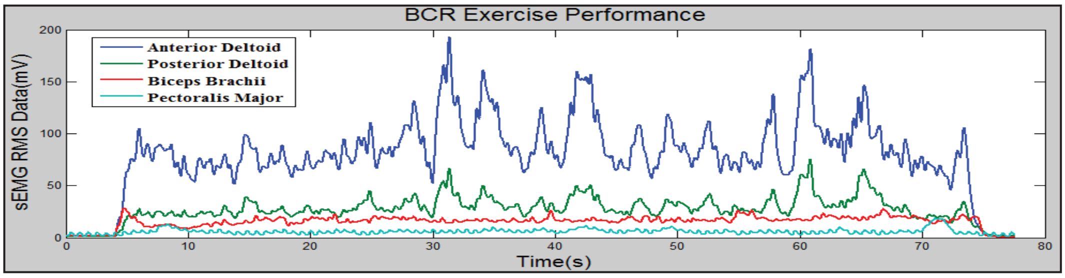
(a) Ping Pong Rehabilitation Exercise



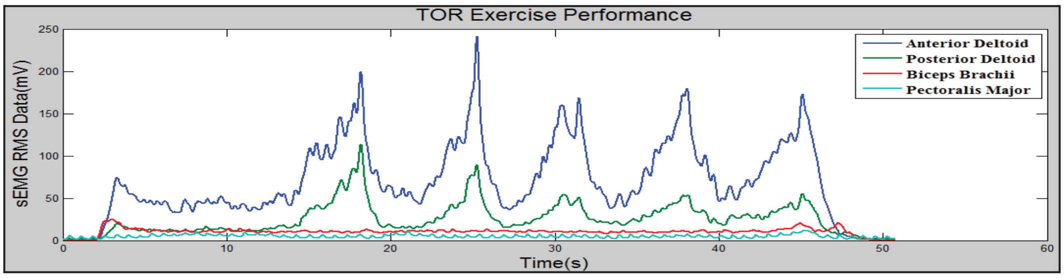
(b) Circular Motion Rehabilitation Exercise



(c) Feeding Animal Rehabilitation Exercise



(d) Balloon Collection Rehabilitation Exercise

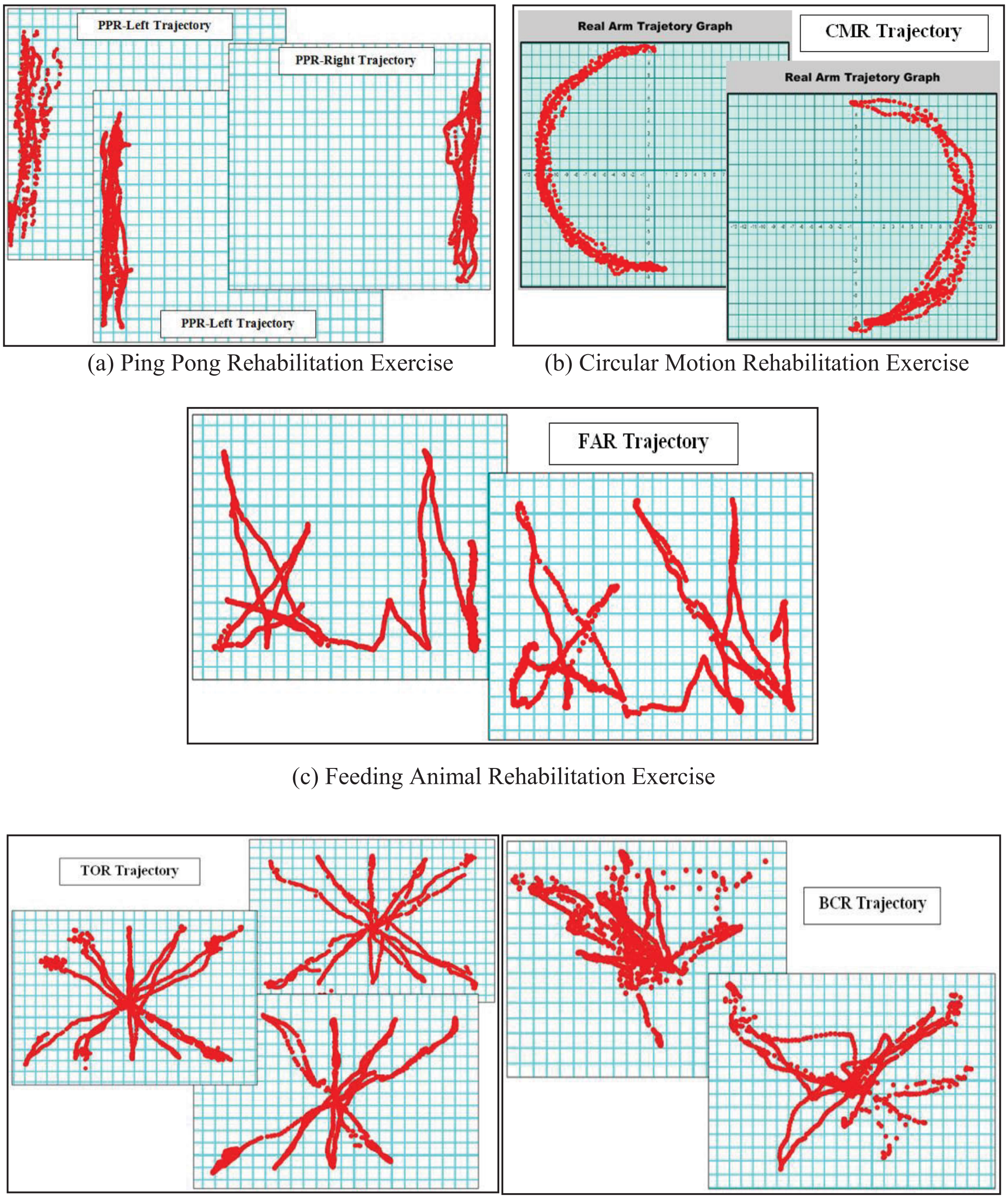


(e) Transfer Object Rehabilitation Exercise

Figure 3-30: Muscle Performance in each Exercise

performance to determine whether the players are able to reach the destination point or only up to the half way of the trajectory.

In RehaBio, all the trajectories are recorded in real-time during the exercises. Some of the trajectory results from the experiment 2 are portrayed in Figure 3.31. These trajectory results demonstrate clearly the performance of actual arm movements. In PPR exercise (both left and right exercises), flexion-extension movements were well performed as shown in Figure 3.31 (a). Similarly, CMR exercises for both left and right exercise were able to move properly without much out of trajectory in Figure 3.31 (b). From FAR



(a) Ping Pong Rehabilitation Exercise

(b) Circular Motion Rehabilitation Exercise

(c) Feeding Animal Rehabilitation Exercise

(d) Balloon Collection Rehabilitation Exercise

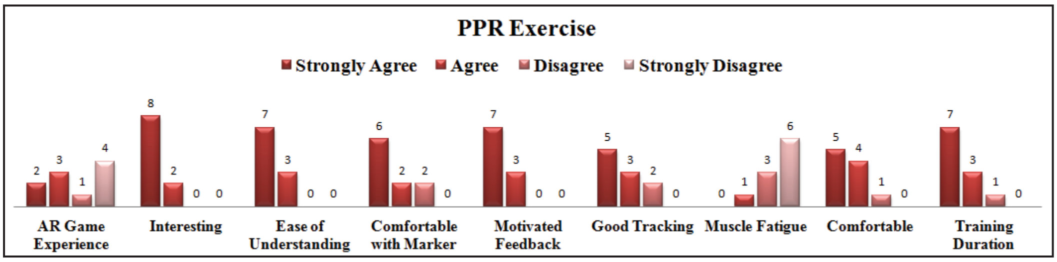
(e) Transfer Object Rehabilitation Exercise

Figure 3-31: Trajectory Performances of each Exercise trajectory graph (Figure 3.31 (c)), it can be clearly seen that on the right side of the graph is the completed exercise while on the left side of the graph is the time out during the exercise. In this way, the performance of the player can be easily traced and evaluated. There are three trials of TOR trajectories which are portrayed in Figure 3.31 (d). It can be clearly seen that only one of the trials completed the exercise and the other two trials were out of time. The last exercise, BCR requires random motion of the upper limb. Hence, the wider the trajectory spread on the trajectory graph, the better recovery for the patient as shown in Figure 3.31(e).

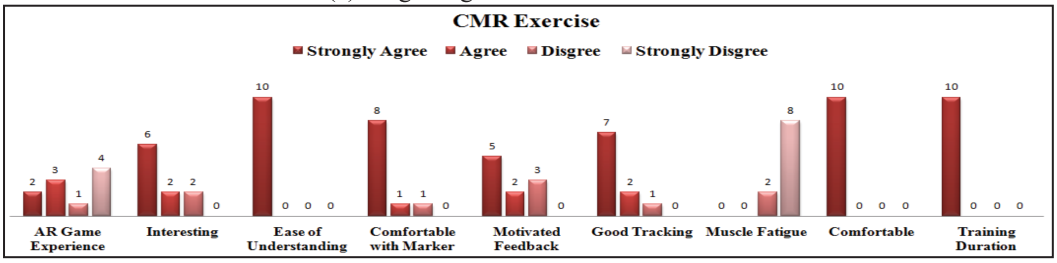
To evaluate the effectiveness in terms of user motivations and enjoyment, a questionnaire was answered by all the participants at the end of each exercise. The set of questions from the questionnaire are describes in the Appendix A3. The score ranking from ‘1’ to ‘4’ where ‘1’ refers to strongly disagree and ‘4’ refers to strongly agree is required to be answered for each question which is stated in the questionnaire. The results from the questionnaire are as shown in Figures 3.32. According to the result, most of the participants found that all the therapeutic exercises were interesting and they enjoyed the exercises without any major discomfort. They all were well informed of the aim and purpose of every exercise before the game play. Most of the participants agreed that all the exercises were very easy to understand with motivating feedbacks. Almost all participants felt that the tracking of the colour marker was good except some of the participants felt that the colour marker was fluctuating but still accomplished the work without any problem. However, some of the participants felt muscle fatigue due to not enough rest between exercises. Most of the participants agreed with the duration of the exercises which were predefined. However some of them requested the custom defined timer and this improvement has been done in the RehaBio system.

3.5.5.5. Experiment 3: Real-Time Muscle Simulation

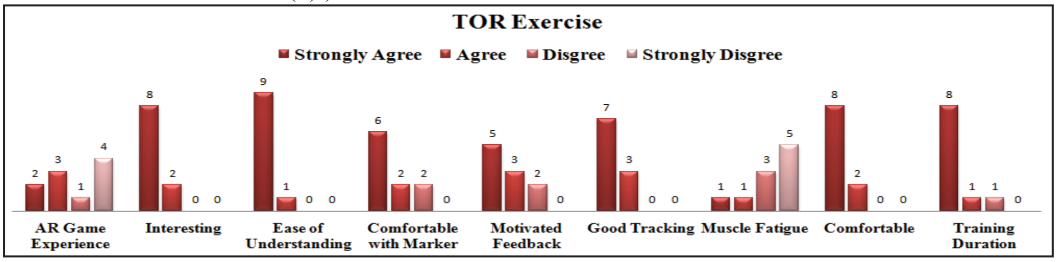
In the third phase of experiment, the evaluation of real-time muscle simulation was conducted. In this experiment, the EMG data that was collected by the FlexComp EMG acquisition device defined each user’s muscle threshold level to perform the muscle simulation. Each of the participants in this experiment was treated as physiotherapist and given the full authority to access both Physiotherapist Interface and Patient Interface in RehaBio system.



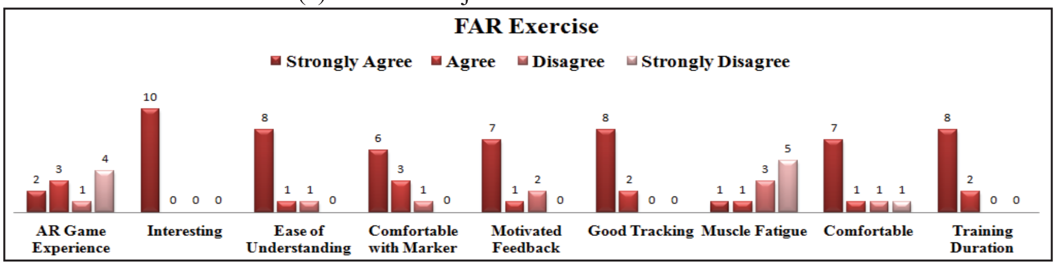
(a) Ping Pong Rehabilitation Exercise



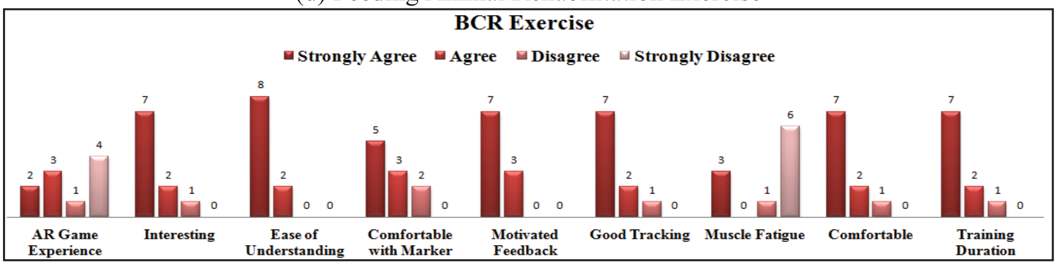
(b)) Circular Motion Rehabilitation Exercise



(c) Transfer Object Rehabilitation Exercise



(d) Feeding Animal Rehabilitation Exercise



(e) Balloon Collection Rehabilitation Exercise

Figure 3-32: Questionnaire results from each Exercise

After having been given the training on how to access the complete RehaBio system the participants found that the manipulation of the RehaBio GUI such as manipulation of database, AR-based rehabilitation exercises and biofeedback simulations is very user friendly. They could manipulate the whole system after one or two training sessions without much problem. In addition to this, the user data under RehaBio database are able to be saved and deleted easily via ‘patient profile’ GUI while physiotherapists/carer are able to retrieve the patients’ performance information via ‘performance result’. ‘Rehabilitation exercises’ under patient interface GUI allows the choices of AR-based rehabilitation exercises easily recommended by the physiotherapist/carer. The participants found that START and STOP buttons from biofeedback simulation were a one touch activation interface that let them manipulate easily for reading and stopping of sEMG data, displaying of real-time sEMG amplitude data and muscle simulation as shown in Figure 3.33. The overall feedback from participants is very encouraging and this motivates us to demonstrate our developments in Port Kembla Hospital to improve our system with the help of clinical specialists which will be discussed in Chapter 5.

3.6. Summary

In this chapter, a novel RehaBio system for upper limb rehabilitation was proposed and developed for paralyzed patients due to any neurological disorder which is the first contribution of this thesis. It was developed by considering ten basic principles of neural

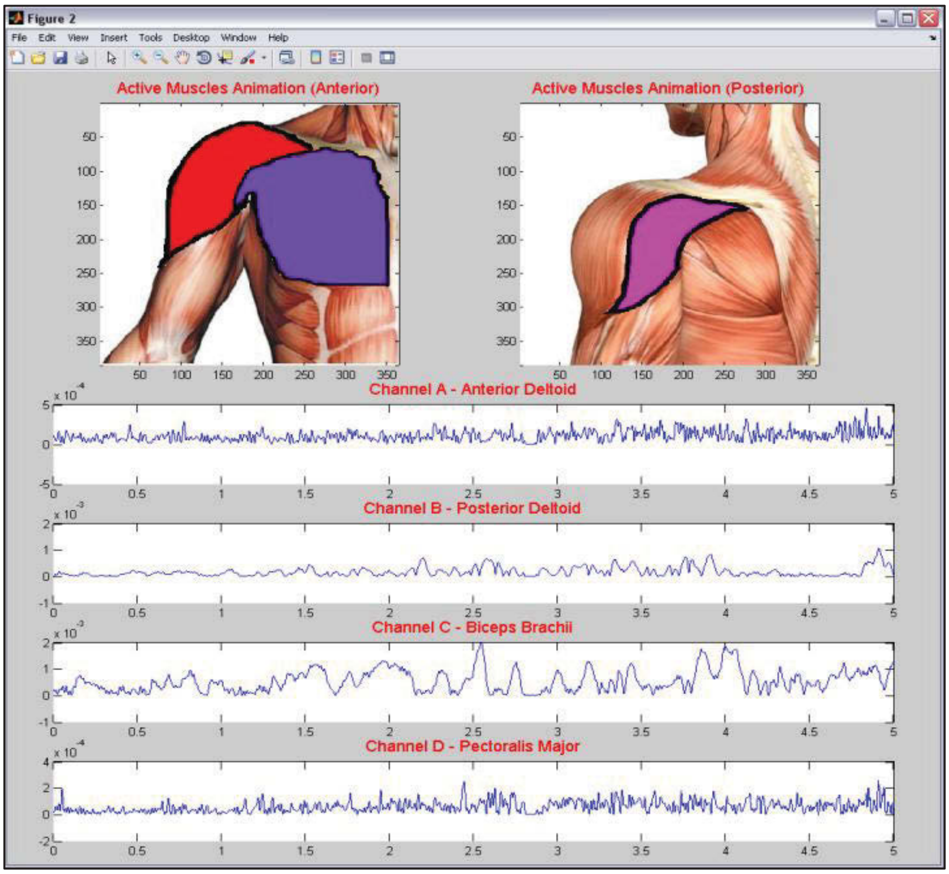


Figure 3-33: Real Time Muscle Simulations Module Graphical User Interface

plasticity that govern learning in both intact and damaged brain. In contrast to robotic based rehabilitation systems or Nintendo Wii based rehabilitation systems, the proposed system in this thesis is very low cost due to the requirements of personal computer and four color markers, any low cost sEMG acquisition device only. In addition to these, patients can practice rehabilitation exercises at home under carer supervision without travelling to rehabilitation hospital and this will help the patients' family on travelling cost especially who are living at rural areas. The complete system was made up of three modules: 1) Database module where patient information and data are stored and able to be tracked easily for their performance along the rehabilitation period, 2) AR based rehabilitation exercises module which is enriched with motivations, feedbacks and information, 3) a real-time biofeedback simulation module where the muscle simulation is set according to the level of muscle activities (threshold level). The detailed developments of each module were thoroughly explained in this chapter with the concept behind the rehabilitation exercise which reference to practical practice where applicable. To evaluate the effectiveness of the developed system, usability tests were conducted and the results were carefully analyzed in terms of Data, Performance (Trajectory) and Questionnaire. From the literatures, the best existing rehabilitation systems only provide either virtual environment with biofeedback system and data glove or pure augmented reality based rehabilitation exercises without any biofeedback to the patients/physiotherapists. Only our proposed rehabilitation system provides complete motivational aspects in terms of augmented reality environment for long term rehabilitation therapy with real-time biofeedback simulation in safe environment and complete database and therefore we cannot benchmark with other current existing system. The complete RehaBio system was demonstrated to the clinical professionals in Port Kembla Hospital. The responses and feedback from the professionals were very promising and encouraging for the neurological disorder patients. As this is the ongoing research, to provide an effective rehabilitation product for professionals and patients, clinical trials are on the way to validate the effectiveness of the RehaBio system.

Chapter 4

Real Time Biosignal Driven Virtual Human Arm

4.1. Introduction

Myoelectric signals from surface electromyography (sEMG) are very useful and important signals to extract the intention of oneself because the signal is able to indicate the intention of movement even before the actual movement is happening [219].Therefore, numerous sEMG based rehabilitation systems especially to predict the intention of oneself movement have been the focus of research in recent years. In this context, various prediction control methods based on sEMG have been proposed such as joint torque prediction, force estimation and joint angle prediction. Some of the prediction methods were developed with additional inputs such as sensors and/or commercially available consoles . Among these prediction methods, joint angle prediction is the most direct estimated output to drive the rehabilitation system. One of the major challenges in developing such predicted controllers is estimating the user intention continuously based on sEMG signal in real time. Common issues related to this challenge are degradation of model accuracy along with computation time, electrode placements and alteration of limb posture. In order to accommodate these issues, signals processing and statistical modeling for estimation of joint angles based on sEMG are essential. In this context, machine learning regression methods have proven to be viable methods for estimating or predicting the user actions by means of sEMG signals. Among several possible approaches for estimating the joint angle in real time, artificial neural (ANN) network is the most popular method. From literatures, it is shown that extreme learning machine (ELM) tends to be outperformed by any other machine learning methods in terms of generalization performance and learning speed.

The objectives of this chapter are twofold. Firstly, the motions of a virtual human arm (VHA) model are controlled in real time by a user's own biological signals. In other words, the optimal controller for VHA is necessary to be developed in which it can predict the user intention by converting the recorded sEMG signals into joint angles in real time. This objective is achieved via thorough selection of muscle parameters and neural-muscle activation coefficients which are discussed in detail in section 4.2. Secondly, the realistic VHA model is developed so that the kinematic and kinetic behavior of the VHA is mimicking the user's arm articulations. In addition, the simulation of the VHA model must update with the new position on the display screen within an interval of time near to or less than that governed by the flicker fusion frequency. This is to ensure that movement between frames appears smooth without noticeable transitions. Therefore, all the calculations from the optimal controller and updating of the new pose of VHA must be completed in less than 40 ms for the semblance of real time, smooth and life-like motion [152].

4.2. Relationship between Neural Command and Muscle Activation

Motor tasks are usually commanded by the nervous system which generates an appropriate temporal pattern of muscle activations. This is done via a dynamical neuronal system where a static representation of the sensory information translates into time varying muscle activations. Therefore, it is important to study and understand the relationship between neural command and muscle activation in order to develop the neural-muscle activation (NMA) model to use in a control algorithm. With respect to this relationship, electromechanical delay (EMD) is one of the important parameters to consider as this greatly impacts on the performance of a biosignal driven control algorithm.

4.2.1. Electromechanical Delay

For any neural command to generate the activation on the muscle there is a motor execution time, which is known as EMD. It has been considered to be influenced by several structures and mechanisms such as the propagation of the action potential and the excitation-contraction coupling processes (E-C coupling) and the muscle force transmission along the series elastic component(SEC) [220]. The studies have shown significant changes in EMD by experimental manipulation of the tension in SEC and hence this is the primary determinant of the EMD [221]. In addition, all the structures of SEC, classically composed of an active part (which is located in myofibrils) and a passive part (mainly aponeurosis and tendon) could contribute differently to EMD [222]. There are three major areas of study in terms of EMD. The first area is the changes in reaction time based on the performance of different tasks [223, 224]. The second area is to study the significant changes of EMD in muscles under different tasks [221, 225]. The last area is to study the differences in EMD for different populations [226, 227]. From literatures, the rate of force production is the parameter that determines the changes in reaction time as well as the EMD value and is much dependent on types of contractions such as isometric, isotonic, fatigued and non-fatigued contraction. In addition to that, the EMD is also different in male, female, neurologically impaired and normal populations. Therefore, EMD is a user dependent parameter and it is necessary to be analysed individually for specific task; in general it varies between 10 and 100 ms for skeletal muscles [228] depending on the intended task. The mathematical formula for EMD (d) can be defined as the time between the first discernible electrical activity in a muscle (t_{emg}) and the first detectable mechanical response (t_{mr}) as follow:

$$d = t_{mr} - t_{emg} \tag{4.1}$$

4.2.2. Muscle Activation Model

After considering the EMD, the next step is to find out the activation model in the form of a mathematical model. The transformation of EMG to muscle activation is modeled by Zajac using the first-order linear differential equation as follow [222]:

$$\frac{d\,u(t)}{dt} + \left[\frac{1}{\tau_{act}} . \left(\beta + (1-\beta)e(t)\right)\right] . u(t) \frac{1}{\tau_{act}} . e(t) \tag{4.2}$$

where $u(t)$ is muscle activation, $e(t)$ represents input EMG, τ_{act} represents time delay for muscle activation and β is the coefficient that defines the first-order system. However, sEMG are generally acquired at discrete time intervals and these discretized data work more efficiently with a second-order relationship. Therefore, a discrete version of second-order differential equation was proposed with an additional step, neural activation, $n_k(t)$, between input EMG and muscle activation by Buchanan et al., as follow [229]:

$$n_k(t) = \lambda\, emg_k(t-d) - \mu_1 n_k(t-1) - \mu_2 n_k(t-2) \qquad (4.3)$$

where $emg_k\,(t - d)$ is processed sEMG signal of muscle k at time t, d is EMD and λ, μ1, and μ2 are the recursive coefficients with constraints to ensure the stability of the equations as follow:

$$\begin{gathered} \mu_1 = \gamma_1 + \gamma_2 \\ \mu_2 = \gamma_1 \cdot \gamma_2 \\ |\mu_1| < 1,\ |\mu_2| < 1 \end{gathered} \qquad (4.4)$$

In addition to that, equation (4.2) can be seen as a recursive filter and thus, this filter should have unit gain for its maximum neural activation value. Therefore, the following constraint is imposed:

$$\lambda - \mu 1 - \mu 2 = 1 \qquad (4.5)$$

Although some muscles have linear isometric between EMG and muscle activation, there are nonlinearity conditions for other muscles. This nonlinear action between neural activation, $n(t)$ and muscle activation, $u(t)$ can be modeled as:

$$u_i(t) = \frac{\left(e^{A_i \cdot n_i(t)} - 1\right)}{\left(e^{A_i} - 1\right)} \qquad (4.6)$$

where $u_i(t)$ is muscle activation for muscle "i" at time "t" and the A_i coefficient is a nonlinear shaping factor specific to muscle "i". A_i is varied between -3 and 0 where $A_i = -3$ means highly exponential and $A_i = 0$ means a linear relationship.

The output of the activation model is input for the biosignal driven controller. In this chapter, two control methods are studied and developed and one is chosen as an optimal controller for virtual model simulation. These control methods are based on backpropagation neural network (BPNN) and extreme learning machine (ELM).

4.3. Description of BP Algorithm in Mathematics

First step: Forward Propagation

The three-layered BP network with x input sites, y hidden, and z output units are considered to describe the mathematical computations. The weight between input site i and hidden unit j will be called w_{ji} and the weight between hidden unit j and output unit l will be called v_{lj}. This three-layered network is illustrated in Figure 4.3.

The output of the note of hidden layer is defined as:

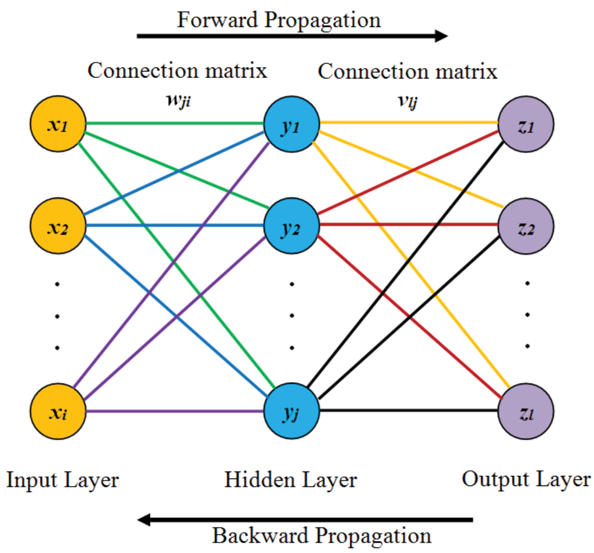


Figure 4-1: Notation for three-layered network

$$y_j = \varphi(net_j) \tag{4.7}$$

where $net_j = \sum_i w_{ji} x_i$.

The output of output node is defined as:

$$z_j = \varphi(net_l) \tag{4.8}$$

where $net_l = \sum_j w_{lj} y_j$.

The square error function in BPNN is given as:

$$E = \frac{1}{2}\sum_l (t_l - z_l)^2 = \frac{1}{2}\sum_l \left(t_l - \varphi\left(\sum_j v_{lj} y_j\right)\right)^2$$

$$= \frac{1}{2}\sum_l \left(t_l - f\left(\sum_j v_{lj}\, \varphi\left(\sum_i w_{ji} x_i\right)\right)\right)^2 \tag{4.9}$$

where E is the square error, t is the target output for a training example, z is the actual output from the output neuron and φ is the activation function. The factor $\frac{1}{2}$ is added to cancel the exponent when differentiating.

Second step: Backward Propagation

In this propagation, the weight value is regulated for all layers. The calculation of the partial derivation of output node by means of error function is done using the chain rule as follows:

$$\frac{\partial E}{\partial v_{lj}} = \sum_{k=1}^{n} \frac{\partial E}{\partial z_k} \cdot \frac{\partial z_k}{\partial v_{lj}} \tag{4.10}$$

Although E is a function containing several z_k, only z_l is related with v_{lj} and therefore all the z_k are independent from each other and this becomes:

$$\frac{\partial E}{\partial v_{lj}} = \frac{\partial E}{\partial z_l} \cdot \frac{\partial z_l}{\partial v_{lj}} \tag{4.11}$$

The last term of the right-hand side can be rewritten using the chain rule as follows:

$$\frac{\partial z_l}{\partial v_{lj}} = \frac{\partial z_l}{\partial net_l} \cdot \frac{\partial net_l}{\partial v_{lj}} = \varphi' \left(net_l\right) . y_j \tag{4.12}$$

The first term of the right-hand side is straightforward to evaluate as follows:

$$\frac{\partial E}{\partial z_l} = \frac{1}{2} \sum_k \left[-2 \left(t_k - z_k\right) . \frac{\partial z_k}{\partial z_l} \right] = -\left(t_l - z_l\right) \tag{4.13}$$

Therefore, by substituting equation (4.12) and (4.13) to (4.11), it becomes:

$$\frac{\partial E}{\partial v_{lj}} = -\left(t_l - z_l\right) . \varphi'\left(net_l\right) . y_j \tag{4.14}$$

Lets the error of input node be δ_l which is defined by

$$\delta_l = \left(t_l - z_l\right) . \varphi' \left(net_l\right) \tag{4.15}$$

By substituting equation (4.15) to (4.14), it becomes:

$$\frac{\partial E}{\partial v_{lj}} = -\delta_l \, . \, y_j \tag{4.16}$$

After finding the error function of the output node, the error function of the hidden layer can be computed as follows:

$$\frac{\partial E}{\partial w_{ji}} = \sum_l \sum_j \frac{\partial E}{\partial z_l} \cdot \frac{\partial z_l}{\partial y_j} \cdot \frac{\partial y_j}{\partial w_{ji}} \tag{4.17}$$

where E is the error function which consists of several z_l; it is targeted at certain w_{ji}, corresponding to one y_j. From equation (4.17), $\frac{\partial E}{\partial z_l}$ can be calculated as:

$$\frac{\partial E}{\partial z_l} = \frac{1}{2} \sum_k \left[-2\,(t_k - z_k).\frac{\partial z_k}{\partial z_l} \right] = -\,(t_l - z_l) \tag{4.18}$$

By substituting equation (4.18) into (4.17) and solving it, the output will give as follows:

$$\begin{aligned} \frac{\partial E}{\partial w_{ji}} &= -\sum_l (t_l - z_l)\,.\,\varphi'(net_l).\,v_{lj}.\,\varphi'(net_j).\,x_i \\ &= -\sum_l \delta_l v_{lj} \varphi'(net_j).\,x_i \end{aligned} \tag{4.19}$$

Let the error of hidden layer node be δ'_j with given equation (4.20) as follows:

$$\delta'_j = \varphi'(net_j).\sum_l \delta_l v_{lj} \tag{4.20}$$

By substituting equation (4.20) into (4.19), the final outcome will be given as equation (4.21):

$$\frac{\partial E}{\partial w_{ji}} = -\delta'_j x_i \tag{4.21}$$

Third Step: Weight updates

After computing all the partial derivatives the network weights are updated in the negative gradient direction in order to update in the direction of the minimum of the error function. The learning constant η defines the step length of the correction. The corrections for the weights are given by

$$\Delta v_{lj} = -\eta\,\frac{\partial E}{\partial v_{lj}} = \eta \delta_l y_j \tag{4.22}$$

and

$$\Delta w_{ji} = -\eta'\,\frac{\partial E}{\partial w_{ji}} = \eta' \delta'_j x_i \tag{4.23}$$

It is very important to perform the corrections to the weights only after the backpropagated error has been computed for all units in the network. Otherwise the corrections become intertwined with the backpropagation of the error and the computed corrections do not correspond any more to the negative gradient direction.

4.3.1. Limitations and Improvements

Although BP network is adopted in most of the NN models, there are still inevitable defects in its algorithm such as the convergence rate is rather slow, the network tends to have more redundancy and the gradient descent algorithm converges to local minima as illustrated in Figure 4.2. In order to tackle these limitations, several tricks and methods have been proposed including momentum term [230] and variable learning rate [231-233].

4.3.2. Momentum terms

When the minimum of the error function for a given learning task lies in a narrow valley, following the gradient direction can lead to wide oscillations of the search process. Therefore, the weight behaves as if it had some inertia or 'momentum'. By introducing the momentum term, α it could help to avoid excessive oscillations in narrow valleys of the error function which will result in preventing the learning process from settling in a local minimum. Furthermore, it will accelerate the learning process by encouraging the weight changes to continue in the same direction with larger steps. The example of a network without and with momentum is depicted in Figure 4.3 [234]. The gradient of the error function is computed for each new combination of weights instead of just following the negative gradient direction; a weighted average of the current gradient and the previous correction direction is computed at each step. The adjustment of weight value that includes the additional momentum coefficient is given by

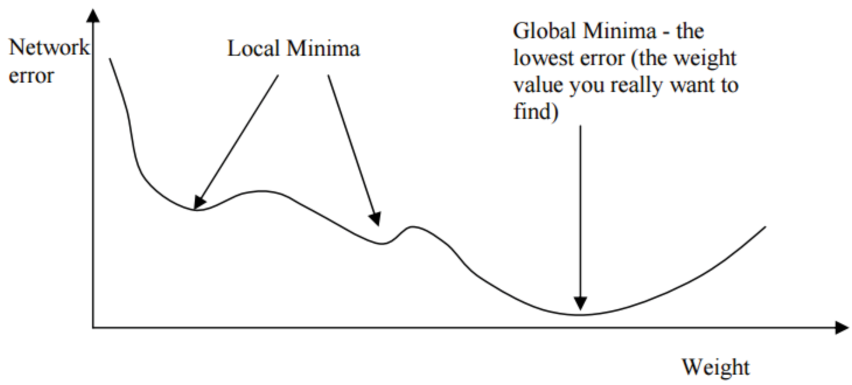


Figure 4-2: Local minima

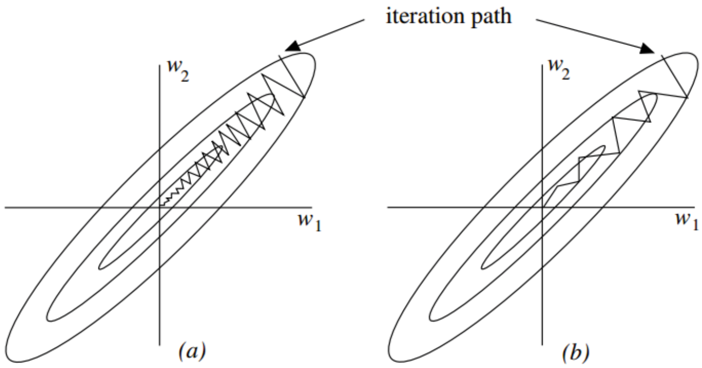


Figure 4-3: Backpropagation network (a) without momentum term and (b) with momentum term

$$\Delta w(t+1) = \alpha\, \Delta w(t) - \eta \frac{\partial E}{\partial w} \tag{4.24}$$

where $\Delta w(t)$ and $\Delta w(t+1)$ represent the weight corrections after the tth and (t+1)th iteration, α is the momentum coefficient with the value of between 0 and 1 and $\frac{\partial E}{\partial w}$ represents the gradient of the error sum of squares to weight in the BP algorithm.

4.3.3. Variable Learning Rate

The performance of the network is very sensitive to the proper setting of the learning rate. If the rate is too small, the algorithm will take too long to converge. If the rate is too high, it may oscillate around minimum point and become unstable. Therefore, the optimal learning rate method is necessary to adapt during the training process in such a way that larger learning rate shall be selected for the areas whose error surfaces are very smooth, and the smaller learning rate shall be selected for the areas whose error surfaces are very precipitous. Although many algorithms have been proposed to deal with the problem of appropriate weight update, most of the approaches lead to the problem of 'blurred adaptivity' due to the size of the actually taken weight step, Δw is not only depended on the adapted learning rate, but also on the partial derivative, $\frac{\partial E}{\partial w}$. In order to overcome this, Riedmiller and Braun [233]proposed resilient propagation (RPROP) learning scheme that performs a direct adaptation of the weight step based on local gradient information. In their proposed algorithm, the adaptive value evolves during the learning process based on the following learning rule:

$$\eta(t+1) = \begin{cases} \Psi^{+}\ \eta(t), & if\ E(t+1) < E(t) \\ \Psi^{-}\ \eta(t), & if\ E(t+1) > E(t) \\ \eta(t), & otherwise \end{cases} \quad (4.25)$$

where $0 < \Psi^{-} < 1 < \Psi^{+}$.

The first term on the right hand side of equation (4.25) represents the situation if the total error sum of squares at $(t+1)^{th}$, $E(t+1)$ increases by less than total error sum of squares at t^{th}, $E(t)$, the weight update is accepted. In this case, the learning rate is increased by some factor, i.e., $\Psi_{inc} > 1$ and the momentum term is reset to its original value if it has been set to '0'. The second term represents the situation if the error $E(t+1)$ increases by more than $E(t)$, the weight update is discarded and the learning rate is decreased by some factor ($0 < \Psi_{dec} < 1$) with momentum term '0'. In the third case, if the error decreases, the weight update is accepted and both learning rate and momentum term are unchanged. However, if the partial derivative changes sign, i.e., the previous step was too large and the minimum was missed, the previous weight update is reverted as follows:

$$\Delta w(t+1) = -\Delta w(t), \qquad if\ E(t+1) > E(t) \quad (4.26)$$

In this method, the number of learning steps is significantly reduced and computation expense of the RPROP adaption process is considerably smaller which leads to an efficient and transparent adaption process for BPNN.

4.4. Description of ELM Algorithm in Mathematics

In order to train the SLFN, popular BP learning algorithm where gradients can be computed efficiently by propagation from the output to the input can be used as shown in section 4.3.1.1. However, it was found that there are some limitations due to gradient-based algorithms. Although the limitations of the BP learning algorithm were improved by several methods, in some cases, the network performance is still affected. In order to overcome this, ELM algorithm was introduced to tackle the BPNN limitations. The overall ELM algorithm can be summarized as in algorithm 4.1.

The output function of the ELM for generalized SLFNs is given by

$$f_l(x) = \sum_{i=1}^{N} \beta_i h_i(x) = h(x)\beta \tag{4.27}$$

where $\beta = [\beta_1, \dots, \beta_N]^T$ is the vector of the output weights between the hidden layer of N nodes and the output node and $H = [h_1(x), \dots, h_N(x)]$ is the hidden layer output matrix the hidden layer with respect to the input x. The *h(x)* actually maps the data from the d-dimensional input space to the *N*-dimensional hidden-layer space ***H***, and therefore, *h(x)* is indeed a feature mapping. In contrast to BP learning algorithm, in ELM, the input weights $\boldsymbol{w_i}$ and the hidden layer biases $\boldsymbol{b_i}$ are not necessarily tuned and randomly assign in the beginning of learning which is given by

$$\begin{aligned} &\| H\,(w_1, \dots, w_{\widetilde{N}}, b_1, \dots, b_{\widetilde{N}})\,\hat{\beta} - T \| \\ &\qquad = min_{\beta} \| H\,(w_1, \dots, w_{\widetilde{N}}, b_1, \dots, b_{\widetilde{N}})\,\beta - T \| \end{aligned} \tag{4.28}$$

If the number $\widetilde{N}$ of hidden nodes is equal to the number of N of distinct training samples, i.e., $\widetilde{N} = N$, the matrix ***H*** is square and invertible when the input weight vectors $\boldsymbol{w_i}$ and the hidden biases $\boldsymbol{b_i}$ are randomly chosen and thus SLFNs can approximate these training samples with zero error. However, in general, the number of hidden nodes is much less than the number of distinct training samples, and hence ***H*** is not a square matrix and there may not exist $\boldsymbol{w_i}$, b_i, β_l and this becomes

$$H\beta = T \tag{4.29}$$

where ***T*** is the target. The objective of ELM is to minimize the error and the norm of weight:

$$\text{Minimize: } \|H\beta - T\|^2 \text{ and } \|\beta\| \tag{4.30}$$

For regression purpose, the output function of the ELM in equation 4.27 can be modified into the following equation:

$$f(x) = h(x)\beta = h(x)H^T \left(\frac{1}{C} + HH^T\right)^{-1} T \tag{4.31}$$

where h(x) is a random feature mapping which is given by

$$h(x) = [G(a_1, b_1, x), \dots, G(a_N, b_N, x)] \tag{4.32}$$

where $G(a_1, b_1, x)$ is a nonlinear piecewise continuous function satisfying ELM universal approximation capability and it is randomly generated according to any continuous probability distribution. Such functions can be as follows:

1) Sigmoid function

$$G(a, b, x) = \frac{1}{1 + exp\big(-(a.x + b)\big)} \tag{4.33}$$

2) Gaussian function

$$G(a, b, x) = \exp(-b\,\|x - a\|^2) \tag{4.34}$$

3) Hard-limit function

$$G(a, b, x) = \begin{cases} 1, & if\ a.x - b \geq 0 \\ 0, & otherwise \end{cases} \tag{4.35}$$

4) Multiquadric function

$$G(a, b, x) = (\|x - a\|^2 + b^2)^{1/2} \tag{4.36}$$

Among these available functions, Sigmoid and Gaussian functions are the major hidden layer output functions used in feedforward neural networks. In the case of unknown feature mapping, kernels can be used in ELM with the output function of the ELM becoming as follows:

$$\begin{gathered} f(x) = h(x)\beta = h(x)H^T \left(\frac{1}{C} + HH^T\right)^{-1} T \\ f(x) = \begin{bmatrix} K(x, x_1) \\ \vdots \\ K(x, x_N) \end{bmatrix}^T \left(\frac{1}{C} + \Omega_{ELM}\right)^{-1} T \end{gathered} \tag{4.37}$$

where

$\Omega_{ELM} = H\,H^T : \Omega_{ELM,ij} = h(x_i, x_j)$ and K is a kernel function with

$$K\ (u, v) = \exp(-\gamma\|u - v\|^2) \tag{4.38}$$

In the following sections, the two prediction models based on BPNN and ELM are proposed to predict the real time joint angle continuously. In the proposed attempts, firstly, the best activation model for the neural to muscle activation transformation is proposed as an input for the joint angle prediction model. Secondly, two joint angle prediction models are developed based on BPNN and ELM and the best prediction model is chosen as an optimal controller for the virtual model, VHA in the AR environment. Finally, the development of the VHA model is detailed and simulation of VHA with chosen optimal controller is performed.

4.5. Thesis Contribution-2: Continuous Joint Angle Prediction

The second contribution of this thesis is to develop the joint angle prediction model in real time. Two prediction models are proposed and developed based on well known machine learning regression methods: back propagation neural network (BPNN) and extreme learning machine (ELM). The proposed BPNN based prediction model and ELM based

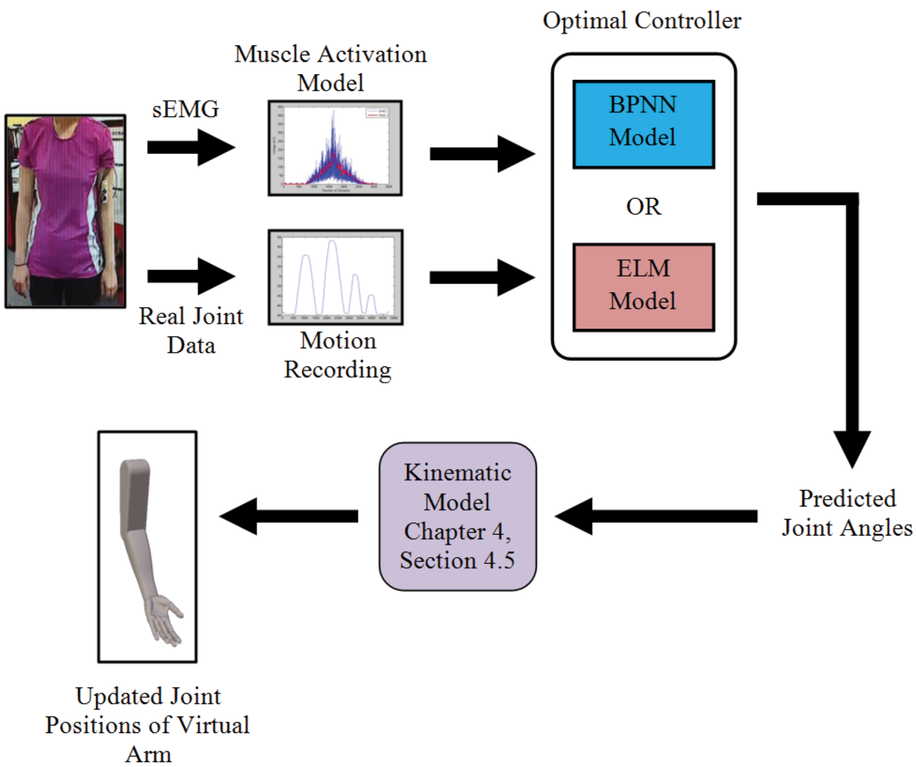


Figure 4-4: The overall concept of proposed real time virtual arm simulation

prediction model had been published in [235, 236] and respectively and [121]. The overall flow-chart that describes the processing steps of the real-time virtual arm is portrayed in Figure 4-4. The real time sEMG signals from user's muscles and actual joint angle data measured from shoulder abduction-adduction and flexion-extension via webcam are inputs for the prediction model. The signals are then feed into the neural-muscle activation model to define the intensity of the muscular contraction. The prediction model then predicts the joint angle values in real time in a continuous manner. Under prediction model, both BPNN and ELM are studied in offline and online mode and the accuracy results are evaluated. Based on the accuracy from the two models, the highest accuracy model is chosen as an optimal controller for VHA model to drive in real-time. The real time results are then fed into the kinematic model to update the current joint position of the virtual arm in the virtual environment.

4.5.1. Neural-Muscle Activation Model

Four sEMG signals from anterior deltoid (AD), posterior deltoid (PD), biceps brachii (BB) and pectoralis major (PM) are chosen to be utilized for angle prediction as these muscles make the most contribution during performing the developed exercises. These finding are based on the experimental results from Chapter 3. The raw signals from the data acquisition device are first pre-processed by band-pass filtering (20Hz – 500Hz) to remove both low and high frequency noise. Afterward, the valuable features are then extracted from these signals with root mean square (RMS) as in chapter 3, equation (1). The sampling rate of 2048 Hz was used in this work. The extracted features are then rectified and normalized by maximum voluntary contraction (MVC). The normalized data are then down-sampled to match the joint angle data which is 200Hz recorded under the motion recording block in Figure 4-4.

The processed data are then sent to equation (4.3) and then to equation (4.6) to compute the neural activation to muscle activation level. Before applying equations, there are several parameters to consider. These parameters include EMD value and recursive coefficients. Since EMD, *d,* value is user and is task dependent, the measurement of *d* is based on individual muscles from each individual participant which is detailed in the experiment section. The selection of the best parameters of recursive coefficients from equation (4.3) is computed by optimization toolbox in Matlab with custom built model.

4.5.2. Motion Recording

The motion of the arm is recorded with Logitech QuickCam E3560 which is attached to the same PC as for the data processing. The markers which are attached to the subject shoulder joint and elbow joint were registered via webcam to track the current position of the subject arm by making use of multi color tracking algorithm which was developed in Chapter 3. From the recorded motion trajectory, the desired joint angle at the shoulder was then calculated. The angle data recording took place in Adobe Flash Professional platform and was recorded in two dimensional (2-D) form as this is adequate to calculate the angles for both shoulder abduction-adduction and flexion-extension motion. The current locations of both the markers were being tracked in every frame and hence, the locations of point A and C from Figure 4.5 were recorded in real time. From these points the absolute length values of AB and BC can be considered. Therefore, the desired joint angle, θ can be calculated by means of trigonometric function which is given by

$$\tan\theta = \frac{opposite}{adjacent} = \frac{BC}{AB} \tag{4.39}$$

The trajectories are sampled at 200Hz with measured units in millimeters. Along with the positions of both markers which are continuously recorded, the shoulder joint angle is calculated continuously.

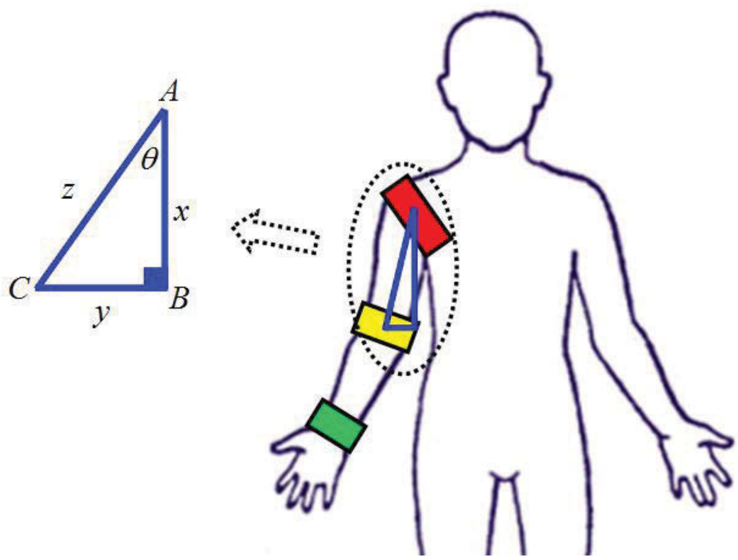


Figure 4-5: Schematic drawing of joint angle recording during shoulder abduction-adduction movement

4.5.3. Proposed Prediction Model with BPNN

The three layers of BPNN controller were developed in Matlab 2013b [237]. The overall structure of the constructed BPNN is portrayed in Figure 4-6. The first layer is an input layer which consists of four nodes for sEMG signals from anterior deltoid (AD), posterior deltoid (PD), biceps brachii (BB) and pectoralis major (PM) muscles. In contrast to traditional BPNN, the input signals of the BPNN are the outputs of the NMA model or traditional time-domain feature (TDF) extraction method.

The second layer is a hidden layer and the performance was evaluated with various numbers of hidden neurons, ranging from 20 to 250 by using fixed training data. In general, the higher the number of neurons in the hidden layer, the higher the accuracy of prediction will be achieved but result in higher computational cost. However, when the accuracy reaches a plateau, only little improvement will be achieved. Therefore the preliminary experiments were performed and it was found that the developed network worked well with 50 neurons. In addition, in order to avoid the overfitting, 70% of the total dataset was used for training and validation and an early stopping method was applied during training iterations [238]. In this layer the Levenberg-Marquardt algorithm was applied due to its fast iteration speed with compatible error result. This algorithm is the combination of Gauss-Newton algorithm and the steepest descent method to take over the speed benefit of the Gauss-Newton algorithm and stability of the steepest descent method.

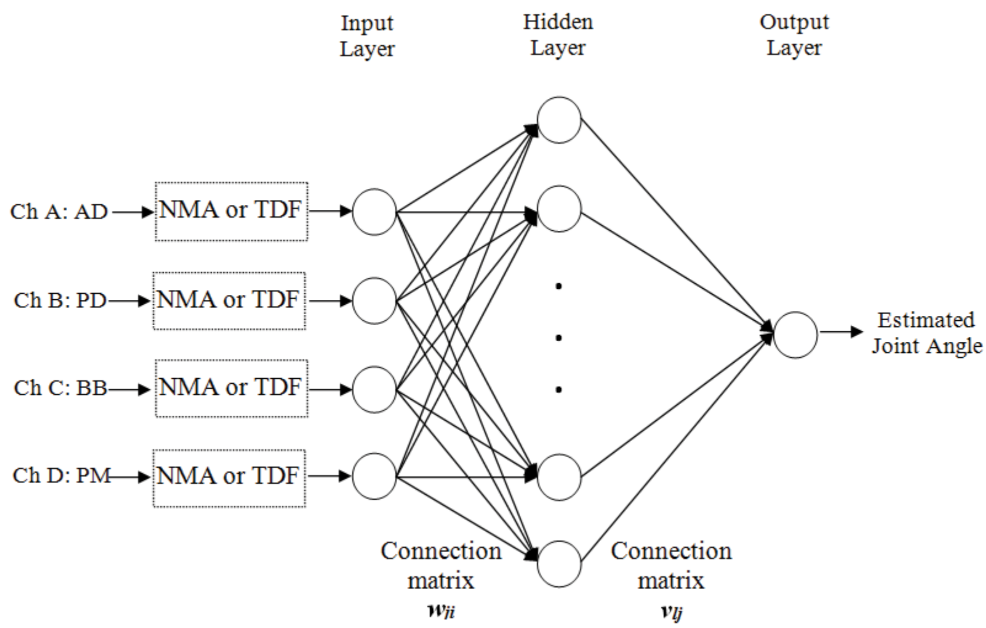


Figure 4-6: Structure of proposed BPNN model

The equation of the Levenberg-Marquardt algorithm is given by

$$w_{k+1} = w_k - (J_k^T J_k + \mu I)^{-1} J_k^T e_k \quad (4.40)$$

During the training process, this algorithm will switch between the steepest decent and the Gauss- Newton algorithm depending on the combination coefficient, μ, as shown in the following equation.

$$\alpha = \frac{1}{\mu} \quad (4.41)$$

If μ is very small, the Gauss-Newton algorithm is used. If μ is very large, the steepest decent method is employed. The equations of the Gauss-Newton algorithm and steepest decent method can be found in equation (4.42) and (4.43).

$$w_{k+1} = w_k - (J_k^T J_k)^{-1} J_k^T e_k \quad (4.42)$$

$$w_{k+1} = w_k - \alpha g_k \quad (4.43)$$

where w is the weight factor, k is the index of iterations, J is the Jacobian matrix, e is a training error and α is the learning constant. The last layer, the output layer, provides the estimated shoulder joint angle for the upper limb. The overall sequence of the BPNN based prediction model is illustrated in Figure 4.7. The developed BPNN was predicted in both offline and online fashion and the experimental results are discussed in section 4.4.5.

4.5.4. Proposed Prediction Model with ELM

Another joint angle prediction model is developed based on the ELM algorithm. The input of the ELM is sEMG signals which are processed by NMA model or traditional feature extraction method. Similar to the BPNN, in this prediction model, four channels from four muscles are employed to predict the user intended motion. In this context, non-kernel based output function (equation (4.31)) is chosen as the feature mapping, ***h(x)*** is known in the developed model. In order to find the best feature mapping for the given inputs to the targets, all the available nonlinear piecewise continuous functions are evaluated in advance. According to the preliminary investigation, the sigmoid function provided a better prediction result compared to other activation functions such as hard-limit, Gaussian and multiquadric. Therefore, the sigmoid function from equation (4.33) is chosen as a

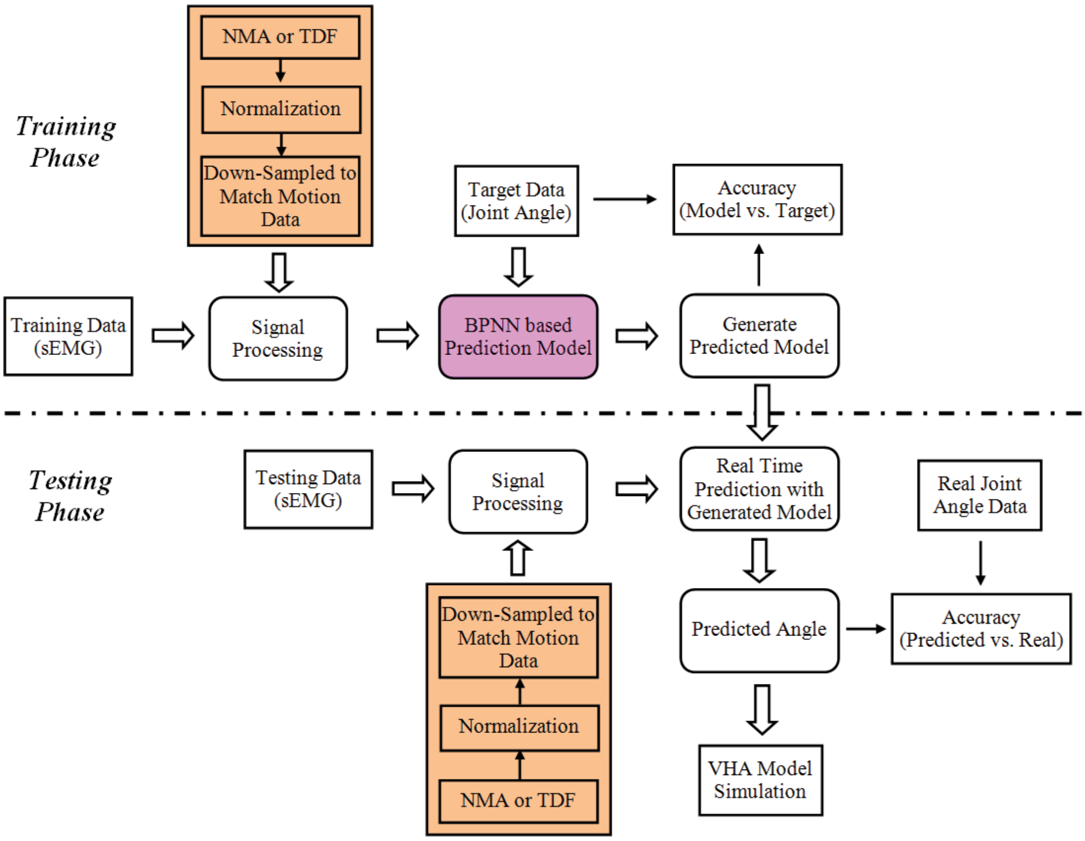


Figure 4-7: Detail sequence of BPNN based prediction model

feature mapping in proposed prediction model. The parameters in the sigmoid function will be randomly generated based on any continuous distribution. Once the parameters are generated, they can be used until the number of input features and number of hidden nodes is changed. After the hidden layer output function has been decided, the number of hidden node (N) and the regularization parameter (C) are then selected empirically. Similar approach to BPNN model is performed with 20 to 250 hidden neurons to find the best performance for ELM model. Although the large value of N is able to provide high accuracy until it reaches plateau, little improvement can be achieved beyond this point. However, the larger the N is, the more memory is required and hence, it is one of the important parameters to identify proper optimal value of N. In the case of parameter C, the optimal range is found to be between 2^2 and 2^8 for this application. Therefore, in this development, the selected values for N and C are 45 and 2^4 respectively and they are used throughout the experiment. In offline mode, 7 out of 10 trials data are trained and validated and the rest are used for testing. In online mode, the trained result from the offline is utilized for real-time prediction. The results from both offline and online testing are discussed in the following sections. The sequence of ELM based prediction model is portrayed in Figure 4.8.

4.5.5. Experiments and Results

In this section, three experiments were conducted to realize the optimal controller for the joint angle prediction. Firstly, the best parameters for the neural-muscle activation model were investigated and then the effectiveness of this model was compared with other traditional time-domain features of EMG via developed BPNN and ELM in offline mode. After that, the performance between BPNN and ELM in online mode was compared to find out the optimal controller for the VHA model.

4.5.5.1. Participants

Fifteen healthy subjects with normal eyesight, sense of touch with mean age of 40 years participated in the experiment. Among them, 14 participants were right handed and one was left handed. All the participants signed an informed consent document to participate in the experiment protocol, volunteering in this study.

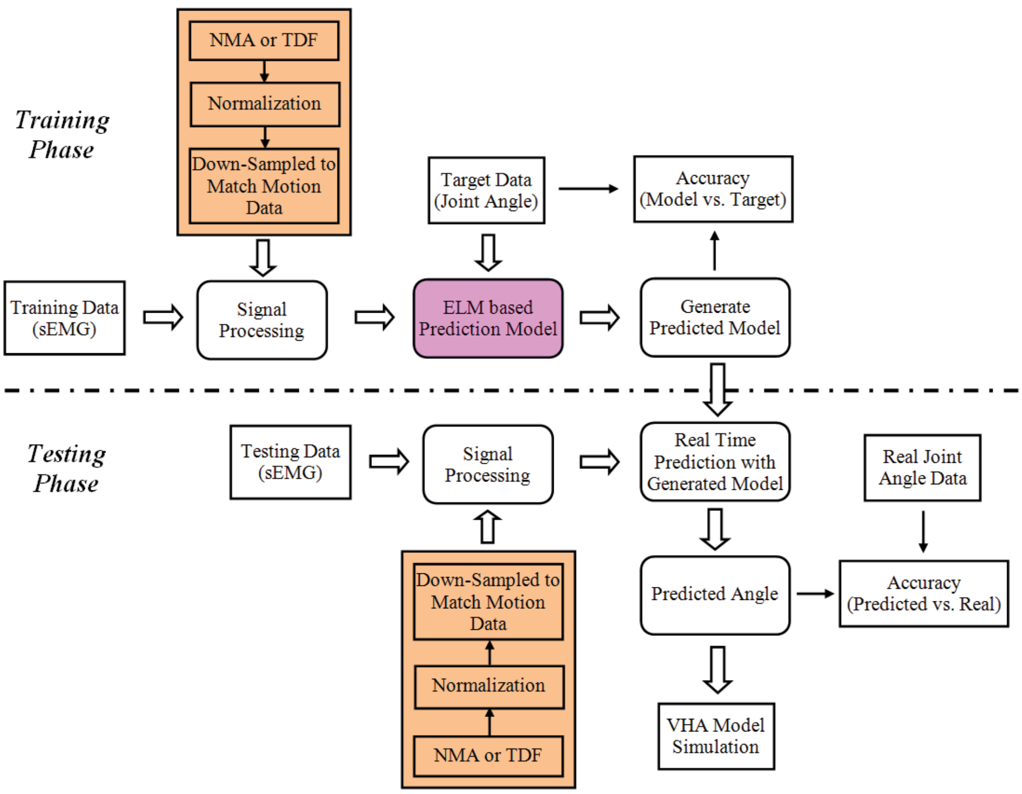
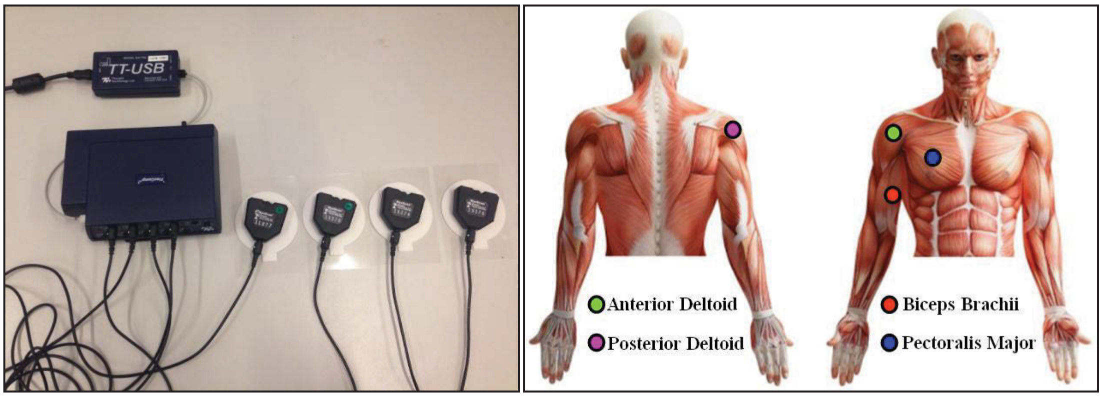


Figure 4-8: Detail sequence of ELM based prediction model



(a) (b)

Figure 4-9: (a) FlexComp System from Thought Technology (b) Locations of the Electrode Sites

4.5.5.2. Data Collection

A commercial sEMG acquisition system, FlexComp, from Thought Technology [212] was used to acquire signals from four channels. Each channel was connected to pre-amplified MyoScan sensors with triode electrodes. It has been shown in Chapter 3 that four extrinsic muscles namely anterior deltoid (AD), posterior deltoid (PD), biceps brachii (BB) and pectoralis major (PM) muscle of upper arm make a large contribution to upper limb articulation for the developed exercises. Therefore, these muscles were targeted as muscles of interest in this study. The skin preparation procedure for non-invasive sEMG was outlined in [239] and was followed to maximize the signal quality in this experiment. The FlexComp system and the locations of the electrode sites are illustrated in Figure 4.9. Two color markers were attached to the user shoulder and the elbow joint. The subjects were requested to sit in front of the desktop to which the webcam was attached at a comfortable height with shoulder 0° abduction, 0° extension and 0° external rotation.

As a very first step, data of both sEMG signals and joint angles were collected from isotonic contraction of studied muscles in offline and online mode. The offline data were used to find out the best parameters and then train the developed prediction models. Based on the offline trained model, offline testing for both prediction models was conducted to choose the optimal model for joint angle prediction. Based on the outcome of testing results from the offline model, the online model was developed to predict the joint angle in real time for the VHA model.

In all modes, all the participants were instructed to move the upper limb at constant velocity in shoulder abduction-adduction from 0° to 170° or up to comfort zone for 10 cycles for 10 trials. Similarly, shoulder flexion-extension from 0° to 180° or up to comfort zone for another 10 cycles for 10 trials were performed. All the participants were allowed to rest anytime between the trials to avoid any muscle fatigue. The data were collected without change in electrode locations in order to maintain consistency between the two different motions. Among the recorded data, 7 trials were used to train and validate the prediction models and 3 trials were used to test in offline mode. As for the online testing, 8 cycles for 5 trials were performed.

4.5.5.3. Experiment-1: Neural-Muscle Activation Model

Before the experiment was conducted, the objective of the experiment was explained to the subjects and a few sessions of training were also given. After that, the data were collected from all the subjects according to the protocol which was described in the data collection section. The collected data were then analysed for EMD value as well as the recursive coefficients for neural-muscle activation (NMA) model. The example EMD result of one subject during isotonic contraction is illustrated in Figure 4.10. The magenta colour is the joint angle measurement and this is when the actual movement of the arm is taking place. As can be clearly seen from the figure, there were some delays between the starting point of activated signals and actual angle: d_{AD}, d_{PD}, d_{BB} and d_{PM} although the intensities of these values were varied. The average EMD values across 15 subjects from two different tasks (abduction-adduction and flexion-extension) are portrayed in Figure 4.11 and Figure 4.12.

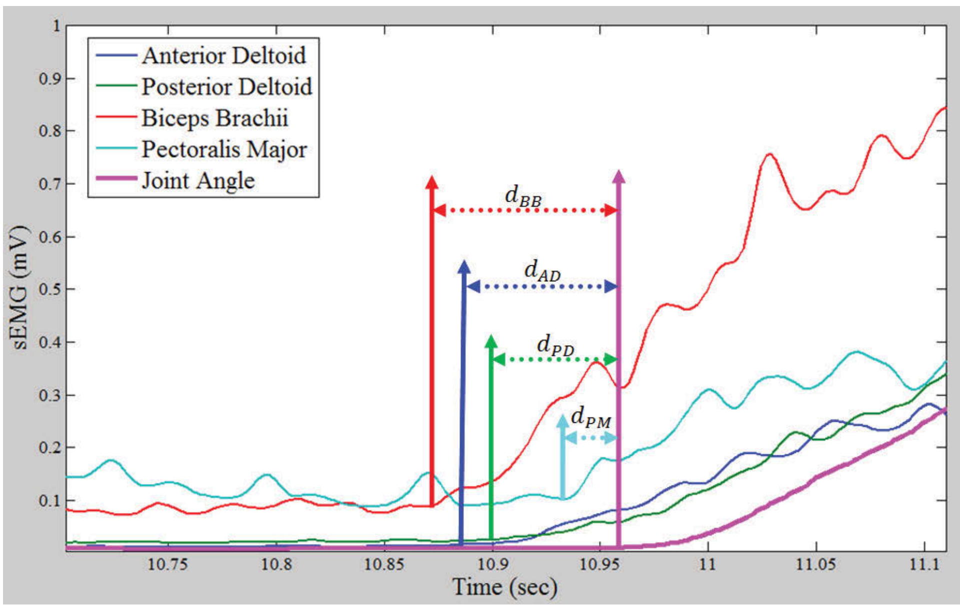


Figure 4-10: Electromechanical delay of one subject during isotonic contraction

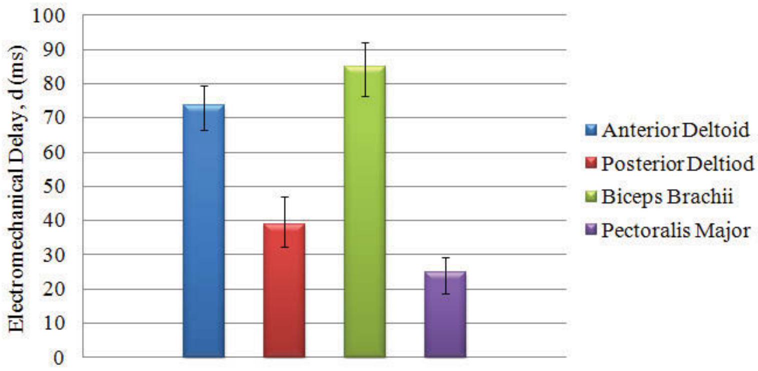


Figure 4-11: Average electromechanical delay value from 15 subjects during shoulder abduction-adduction motion

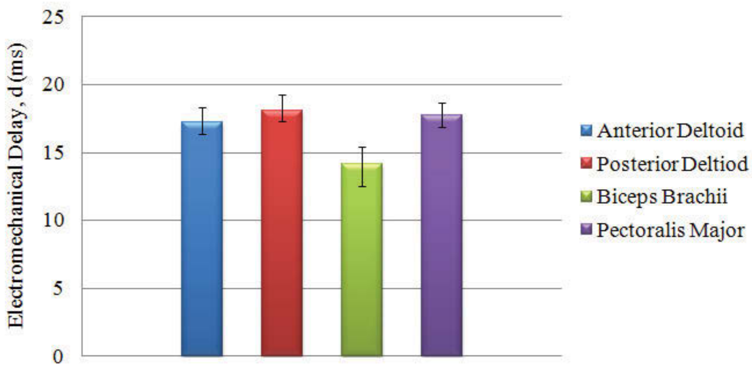


Figure 4-12: Average electromechanical delay value from 15 subjects during shoulder flexion-extension motion

From the graph, the higher EMD values were found during shoulder abduction-adduction compared to that of flexion-extension movement. The one-way ANOVA tests were conducted to compare any significant differences in EMD between different tasks, different muscles and as well as in different subjects. The statistical results from the different tasks revealed that there was significant difference ($p < 0.05$) between the two tasks and hence EMD is actually dependant on the intended task. The analysis from studied muscles showed that there was significant difference across different muscles ($p < 0.005$). This reveals that different muscles possess different EMD values and hence it is important to analyse them individually to attain an accurate prediction model. However, the test results from different subjects provided no significant difference for EMD values during the abduction-adduction task ($p = 0.71$) and flexion-extension ($p = 0.27$) task as all the subjects were requested to perform the tasks at constant speed across the trials and they tried to do so.

After finding the ***d*** value, the best coefficients for both γ_1 and γ_2 were investigated via curve fitting tool with custom made equation based on equation 4.3. The effectiveness of the developed neural-muscle model in the prediction process was also evaluated via comparing with traditional time-domain feature (TDF) extraction methods and these will be discussed in the following section.

4.5.5.4. Experiment-2: Prediction Models in Offline Mode

In this experiment, the offline predictions methods were carried out for both BPNN and ELM model by comparing NMA, and TDF method. Both BPNN and ELM model were trained and tested with the same samples from recorded data. Firstly, NMA model was employed using the best parameters found in the previous section. The outputs of the NMA model were fed into the developed BPNN to train the network for estimation. The trained networks were then used to predict the joint angle based on the testing data. The same training and testing methods were carried out with TDF. In this TDF, four traditional features, namely Mean Absolute Value (MAV), Waveform Length (WL), Variance (VAR) and Willison Amplitude (WA) were chosen due to better estimation performance [240]. The length of the sliding window was 100ms with 20ms overlap and was employed in this experiment. After BPNN model was tested, the ELM model was trained and tested in a similar fashion. The outputs from the NMA model were fed into the developed ELM model followed by outputs from the TDF were feed into the ELM model. After training and testing for all the studied models and methods had been conducted, the results were evaluated via statistical analysis.

A 5-fold cross-validation procedure was used to evaluate the overall statistical performance for two different prediction models with different feature extraction methods. Two performance indices were chosen to compare the performance of the different models with different input features. These indices include normalized root-mean-squared error (NRMSE) and the adjusted coefficient of determination (R_a^2) [241]. The NRMSE is a dimensionless metric expressed as RMSE over the range of measured angle values for each subject which is given by

$$NRMSE = \sqrt{\frac{\sum_{i=0}^{n}(\theta_a - \theta_e)^2}{n}} \tag{4.44}$$

where θ_a and θ_e are the normalized actual measured and estimated joint angles respectively for sample i, and n corresponds to the total number of tested samples. The R^2 is the measurement of the percentage of variation in the dependent variable, in this case angle, explained by the independent variables, in this case sEMG signals and this is given by

$$R^2 = \frac{\left(\sum_{i=0}^{n}(\theta_a - \mu_a)\ (\theta_e - \mu_e)\right)^2}{\sum_{i=0}^{n}(\theta_a - \mu_a)^2\ (\theta_e - \mu_e)^2} \tag{4.45}$$

where μ_a and μ_e are the normalized actual measured and estimated angles at i^{th} sample to n^{th} samples. However, R^2 has a tendency to overestimate the regression when more independent variables are added to the model. Therefore, adjusted R^2 is introduced for more independent variables which is given by

$$R_a^2 = 1 - \left[\left(\frac{n-1}{n-k-1}\right)\ x\ (1 - R^2)\right] \tag{4.46}$$

The results of NRMSE and R_a^2 test from both BPNN and ELM are illustrated in Figure 4.15 to Figure 4.18. As can be clearly noticed from the figures, the results indicate that the performance of the developed NMA model provides a lower *NRMSE* value than that of traditional time-domain feature extraction method in both estimation models.

In order to prove the statistical significance of this result, one-way ANOVA test was carried out between developed NMA model and TDF extraction method. The test reveals that there is a significant difference for NRMSE between studied methods (p < 0.001). Therefore, the developed model NMA can significantly improve accuracy for joint angle prediction. It was also found that the average value of R_a^2 from Figure 4.13 and Figure 4.16 were significantly higher in the ELM model (0.9 ± 0.035) than in the BPNN model (0.85 ± 0.03) with p-value (p < 0.05). This proves that the developed ELM has better prediction performance in studied motions. The average accuracy between actual angle and estimated angle by ELM is computed and the result reveals that the estimated angle is as high as 96.13% in offline mode. In addition to that the offline computational time for both training and testing of BPNN and ELM models are illustrated in Table 4.1. It was clearly

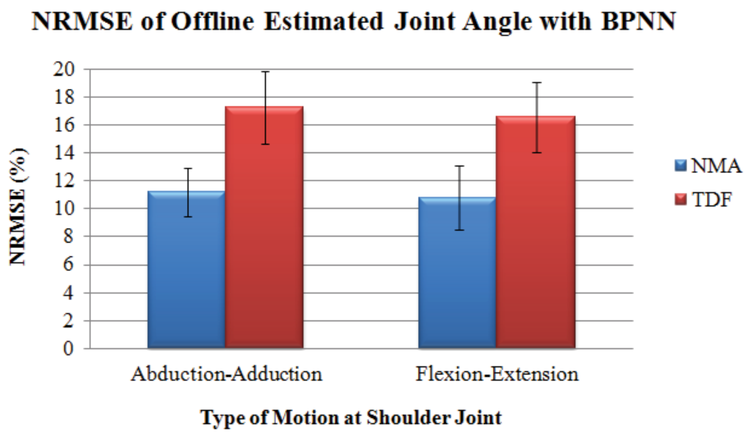


Figure 4-13: NRMSE results of BPNN model during offline estimation

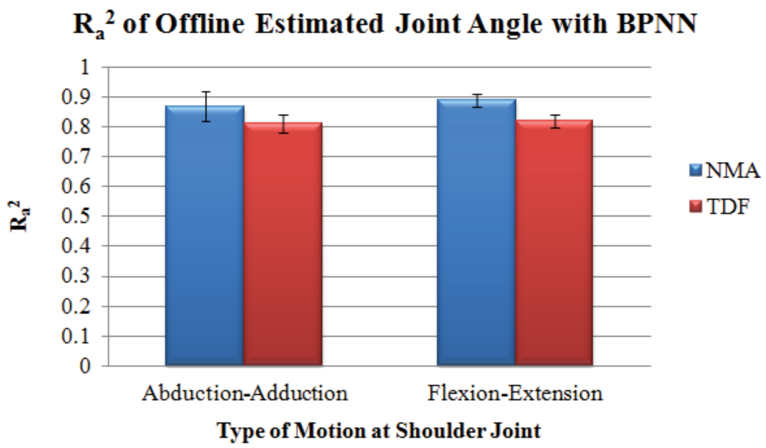


Figure 4-14: Adjusted coefficient of determination of BPNN during offline estimation

seen from the table that during the network training period, ELM has better computational cost than BPNN although there is a compatible duration during testing or prediction with trained network.

Table 4.1: Average offline computational time between BPNN and ELM

Motions	Average Training Time (s)				Average Testing Time (s)			
	BPNN		ELM		BPNN		ELM	
	NMA	TDF	NMA	TDF	NMA	TDF	NMA	TDF
Abd-Add	16.00	19.00	0.17	0.17	0.03	0.04	0.02	0.03
Flex-Ext	15.00	17.00	0.18	0.18	0.03	0.05	0.03	0.03

According to the statistical results, it can be concluded that ELM model with proposed NMA model provides better performance in terms of *NRMSE* and R_a^2 although computational time in testing mode is compatible. Therefore, the online prediction model with ELM has potential to serve as an optimal controller for VHA model in this thesis. To validate this hypothesis, the online experiments were carried out and results were compared which will be discussed in the following section.

4.5.5.5. Experiment-3: Prediction Models in Online Mode

During the online prediction experiments, the real time data from the subject were sent to the trained BPNN and ELM models which were conducted beforehand and predicted the shoulder joint angle in real time continuously. In this experiment, all the participants were requested to perform 8 cycles of shoulder abduction-adduction motion followed by flexion-extension motions with random angles from 0° to 180° with constant velocity for 5 trials. The subjects were free to rest between the trials to avoid muscle fatigue. The offline training was conducted just before the online testing while electrodes were intact. This is to minimize the error due to electrodes position reattachment which will affect the prediction

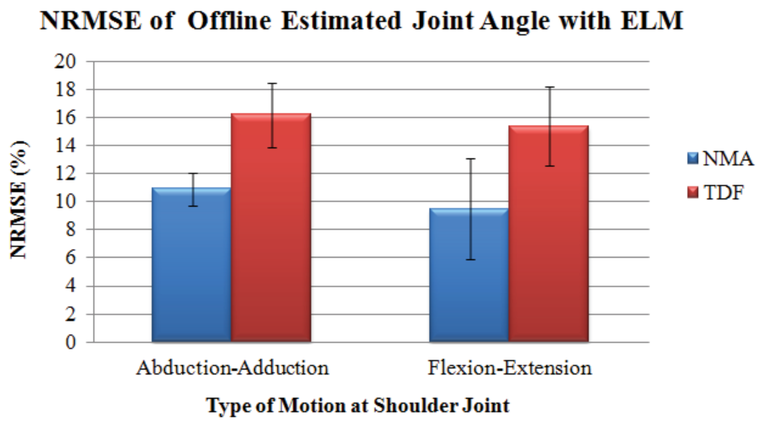


Figure 4-15: NRMSE of ELM model during offline estimation

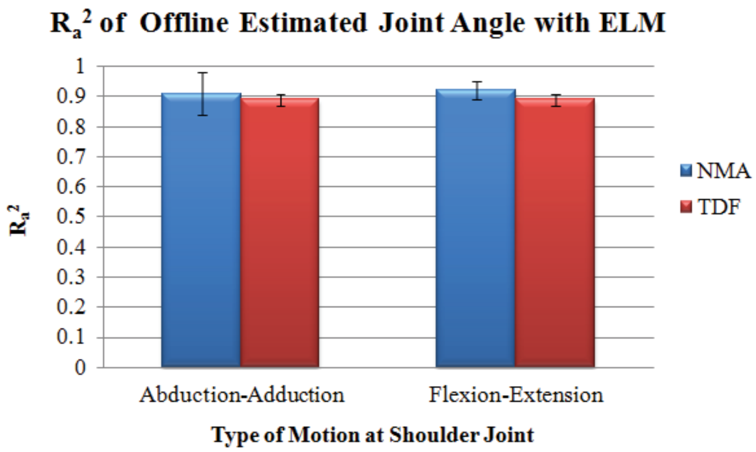


Figure 4-16: Adjusted coefficient of determination of ELM during offline estimation

accuracy. Therefore, the computational time for the offline training was also important in this experiment.

The 5-fold cross-validation of the online testing was performed and the result from one subject in one of the trials was portrayed in Figure 4.17. It was clearly seen form the figure that the developed ELM model (red colour dash line) can predict closer to the targeted angles (blue solid line) than the BPNN model (green solid line). This was because, ELM has better generalization performance than the BPNN in which ELM produces a same result always and therefore consistent and has got better generalization. In addition to this, ELM tends to reach the solutions straightforward without facing several issues such as local minima, improper learning rate and overfitting, etc. In contrast to the requirement of random weights in BPNN algorithm which results in different outputs after each training, ELM always provides same output for a particular input sample. Additionally, NRMSE and R_a^2 were calculated in this experiment to prove the better performance of ELM prediction model over BPNN model and the results are tabulated in Table 4.2. It can be clearly seen from the table that the ELM prediction model provided a better performance than BPNN because error rate of the ELM model is less than that of BPNN model in both shoulder motion cases. Similar to the offline mode estimation, the average accuracy of the predicted joint angles by ELM is computed and it reveals that the estimated angle is as

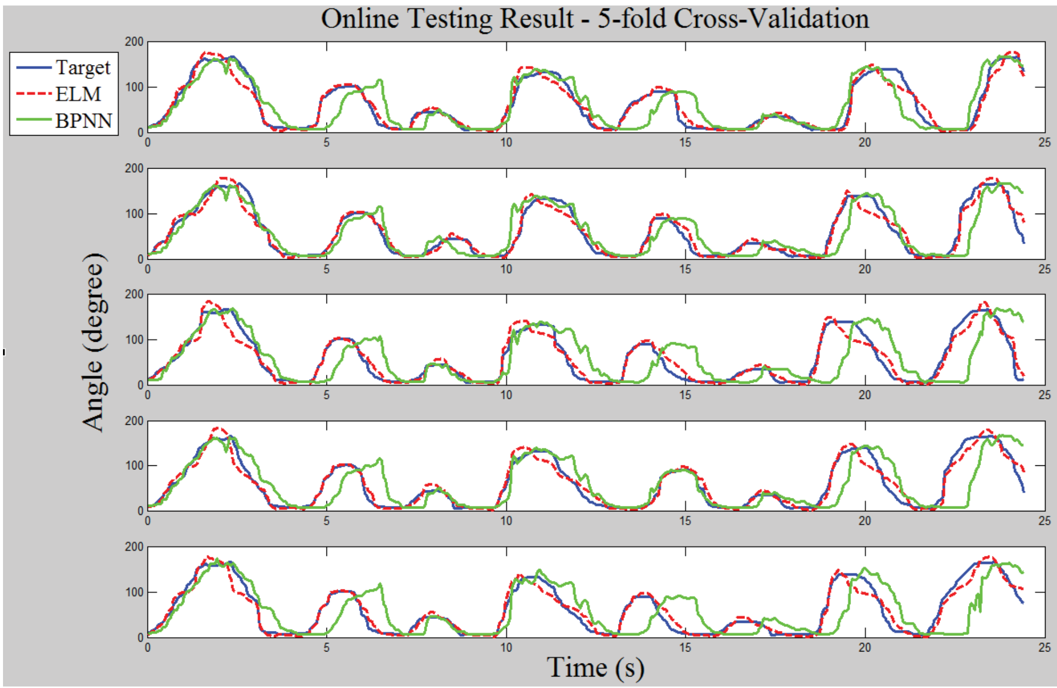


Figure 4-17: Graphical representation of 5-fold cross-validation online result from one of the trials by one subject

high as 93.71% during online mode.

In order to analyse the statistical significance between two regression models, one way ANOVA was carried out across all the trials for all the subjects. The results revealed that there is a significant difference in Ra2 ($p < 0.001$) and NRMSE ($p <0.001$). According to the calculated error results and ANOVA results, it can be concluded that the developed ELM model provides the better prediction results and hence, it is chosen to drive the VHA model from user's sEMG signals.

Table 4.2: Average online prediction results ELM Vs. BPNN

Shoulder Motion	Prediction Model	Model Prediction		Testing Time (ms)
		R_a^2	NRMSE(%)	
Abduction-Adduction	ELM	0.82 (0.02)	15.69 (2.8)	29
	BPNN	0.72 (0.03)	24.33 (1.5)	30
Flexion-Extension	ELM	0.83 (0.05)	14.99 (3.5)	31
	BPNN	0.74 (0.02)	27.15 (1.4)	31

4.6. Thesis Contribution-3: Development of Virtual Human Arm Model

The third contribution of this thesis is the development of a virtual human arm (VHA) model that allows to be utilized for evaluation and verification of theoretical concepts, product designs, analysis and human related pilot operations. In order to simulate the model in a virtual environment, it is important to reproduce a human motion in the computer. In general, there are three major approaches to replicate the human motion in a computer:

1) Motion capture by a real human with a number of sensors that are installed over the entire human body [238];
2) Digital human modeling and motion creation based on pure mathematical algorithms [166];
3) Data insertion between the live motion capture data using a mathematical interpolation [172].

Among the available approaches mentioned above, in this thesis, the combination of motion capture data and mathematical interpolation is employed in order to simulate the virtual model. In addition to this, the biological signals are also employed for simulation of the VHA model to enhance the fast recovery during rehabilitation process. Since the rehabilitation context of this study is focussed on the human upper limb, only virtual human arm (VHA) is developed in this research.

In order to develop the complete upper limb and further to produce a realistic motion, the first step is to understand the upper limb biomechanical information. Human upper limb can be modeled as a set of rigid segments which consists of four segments and these segments are linked by the joints with a total of 7 degrees of freedom (DOFs). Based on this biomechanical information, three-dimensional (3D) graphical representation of the human arm, in this case a VHA model, is developed. Since the purpose of the VHA model is to replicate the articulation of a human arm in realistic form, it is necessary to create two distinct models namely (1) kinematic model and (2) virtual reality model. The detailed descriptions of each model are discussed as follows.

4.6.1. Kinematic Model

In order to model the correct kinematics for the upper limb, actual joints of a human arm are properly investigated. The upper limb can be recognized as a biomedical system which is made up of four rigid links namely humerus, radius, ulna and hand. The connections between these links are shoulder joint, elbow joint and wrist joint. In the case of VHA, these four rigid links are represented as follows: humerus as shoulder, radius and ulna as forearm and hand as hand bodies. In the context of VHA joints, the shoulder joint is represented as a spherical joint which consist of 3DOFs (degrees of freedom): flexion-extension (Flex-Ext), abduction-adduction (Abd-Add) and Medial-Lateral (Med-Lat) rotation, the elbow joint is constructed with a cylindrical joint which allows 1DOF in flexion (Flex) and the wrist joint is constructed with a spherical joint with 3DOFs: flexion-extension (Flex-Ext), abduction-adduction (Abd-Add) and Pronation-Supination (pron-supin) for the forearm. Therefore, the VHA model in this thesis is made up of 7DOFs for its articulations which align and are limited within the normal range of motion as in a real upper limb [242] which is tabulated in Table 4.3. The kinematics of the VHA is modeled with Denavit- Hartenberg (D-H) procedure which is commonly called the D-H convention [243]. In order to calculate the D-H convention in VHA model, a total of four independent parameters: joint angle “$\boldsymbol{\theta}$”, joint offset “$\boldsymbol{d}$”, link twist angle “$\boldsymbol{\alpha}$”, and the link length “$\boldsymbol{a}$” are defined in VHA kinematic chain which is portrayed in Figure 4.18 and Table 4.4.

Table 4.3: Average joint ROM and its comfort zone of human upper limb

<table>
<tr><th>Joint Motion</th><th>ROM (Max°/Min°)</th><th>Confort Zone (Max°/Min°)</th><th>Conditions</th></tr>
<tr><td rowspan="2">Shoulder Flex-Ext</td><td>188 / -61</td><td>65.8 / -21.35</td><td>Elbow neutral 0°</td></tr>
<tr><td>170 / -30</td><td>59.5 / -10.5</td><td>Elbow flexes 90°</td></tr>
<tr><td rowspan="4">Shoulder Abd-Add</td><td>198 / -50</td><td>69.3 / -17.5</td><td>Elbow 0° and Shoulder neutral in vertical</td></tr>
<tr><td>134 / -48</td><td>46.9 / -16.8</td><td>Elbow 0° and Shoulder neutral in horizontal</td></tr>
<tr><td>130 / 0</td><td>45.5 / 0</td><td>Elbow 0° and Shoulder neutral 0°</td></tr>
<tr><td>120 / -30</td><td>42 / -10.5</td><td>Elbow 0° and Shoulder flexes 90°</td></tr>
<tr><td rowspan="3">Shoulder Med-Lat</td><td>90 / -45</td><td>31.5 /-15.75</td><td>Elbow 0° and Shoulder neutral 0°</td></tr>
<tr><td>97 / -34</td><td>34 / -11.9</td><td>Elbow 90° and Shoulder flexes 90°</td></tr>
<tr><td>90 / -90</td><td>31.5 / -31.5</td><td>Elbow 90° and Shoulder abducts 90°</td></tr>
<tr><td rowspan="2">Elbow Flexion</td><td>142</td><td>49.7</td><td>Shoulder neutral 0°</td></tr>
<tr><td><142</td><td>< 49.7</td><td>Shoulder flexes 90°</td></tr>
<tr><td>Joint Motion</td><td>ROM (Max°/Min°)</td><td>Confort Zone (Max°/Min°)</td><td>Conditions</td></tr>
<tr><td rowspan="2">Elbow Pron-Supin</td><td>113 / -77</td><td>39.55 / -27</td><td>Elbow neutral 0°</td></tr>
<tr><td><113 / -77</td><td>< 39.55 / -27</td><td>Elbow flexes 90°</td></tr>
<tr><td>Wrist Flex-Ext</td><td>90 / -81</td><td>45 / -40.5</td><td>N/A</td></tr>
<tr><td>Wrist Rad-Uln</td><td>27 / -47</td><td>13.5 / -23.5</td><td>N/A</td></tr>
</table>

Table 4.4: The D-H parameters for a VHA model

D-H parameters of VHA model				
Joint Name	θi (rad)	αi (rad)	di (cm)	ai (cm)
Shoulder Flex-Ext	$\theta 1$	90	0	0
Shoulder Abd-Add	$\theta 2$	90	0	0
Shoulder Med-Lat	$\theta 3$	-90	*l3*	0
Elbow Flex	$\theta 4$	90	*0*	0
Elbow Pron-Supin	$\theta 5$	90	*l5*	0
Wrist Flex-Ext	$\theta 6$	-90	0	0
Wrist Rad-Uln	$\theta 7$	-90	0	0

4.6.1.1. Forward Kinematics

Based on the D-H parameters from Table 4.4, forward kinematics (FK) of VHA is calculated. This is to find the hand position and orientation in terms of the joint variables by determining a homogeneous transformation A_{i-1}^{i} and this is a product of four basic transformations:

$$A_{i-1}^{i} = Rot_{z,\theta_i} Trans_{z,d_i} Trans_{x,a_i} Rot_{x,\alpha_i}$$

$$A_{i-1}^{i} = \begin{bmatrix} cos\theta_i & -sin\theta_i\, cos\alpha_i & sin\theta_i\, sin\alpha_i & a_i\, cos\theta_i \\ sin\theta_i & cos\theta_i cos\alpha_i & -cos\theta_i sin\alpha_i & a_i sin\theta_i \\ 0 & sin\alpha_i & cos\alpha_i & d \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.47}$$

According to the equation (4.47), the homogeneous transformations of VHA can be found as follows:

$$A_0^1 = \begin{bmatrix} c1 & 0 & s1 & 0 \\ s1 & 0 & -c1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

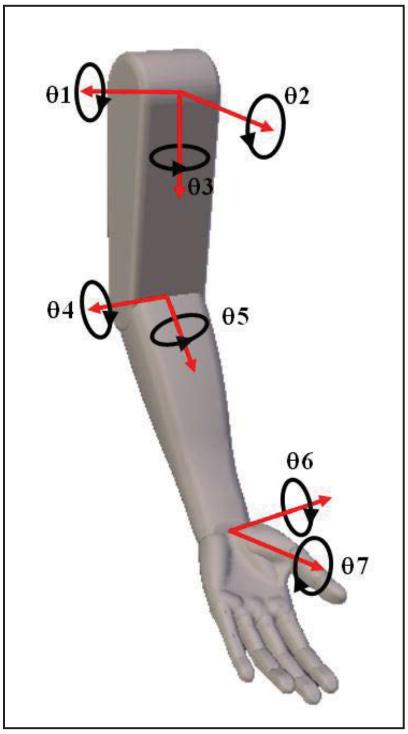


Figure 4-18: Kinematic Chain of Virtual Human Arm

$$A_1^2 = \begin{bmatrix} c2 & 0 & s2 & 0 \\ s2 & 0 & -c2 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$A_2^3 = \begin{bmatrix} c3 & 0 & -s3 & 0 \\ s3 & 0 & c3 & 0 \\ 0 & -1 & 0 & l3 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$A_3^4 = \begin{bmatrix} c4 & 0 & s4 & 0 \\ s4 & 0 & -c4 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$A_4^5 = \begin{bmatrix} c5 & 0 & s5 & 0 \\ s5 & 0 & -c5 & 0 \\ 0 & 1 & 0 & l5 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$A_5^6 = \begin{bmatrix} c6 & 0 & -s6 & 0 \\ s6 & 0 & c6 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$A_6^7 = \begin{bmatrix} c7 & 0 & -s7 & 0 \\ s7 & 0 & c7 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.48}$$

where "c" represents the cosine of θ and "s" represents sine of θ. To compute F-K of the VHA, multiply the A_{i-1}^{i} together and this yields

$$A_0^7 = A_0^1 * A_1^2 * A_2^3 * A_3^4 * A_4^5 * A_5^6 * A_6^7$$

$$A_0^7 = \begin{bmatrix} r_{11} & \mathrm{r}_{12} & \mathrm{r}_{13} & \mathrm{x} \\ r_{21} & \mathrm{r}_{22} & r_{23} & \mathrm{y} \\ \mathrm{r}_{31} & \mathrm{r}_{32} & \mathrm{r}_{33} & \mathrm{z} \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.49}$$

in which

$$r_{11} = c_1c_2c_3c_4c_5c_6c_7 + s_1s_3c_4c_5c_6c_7 - c_1s_2s_4c_5c_6c_7 + s_1c_3s_5c_6c_7 - c_1c_2s_3s_5c_6c_7 + c_1c_2c_3s_4s_6c_7 + s_1s_3s_4s_6c_7 + c_1s_2c_4s_6c_7 - c_1c_2c_3c_4s_5s_7 - s_1s_3c_4s_5s_7 + c_1s_2s_4s_5s_7 + s_1c_3c_5s_7 - c_1c_2s_3c_5s_7$$

$$r_{12} = c_1c_2c_3c_4c_5s_6 + s_1s_3c_4c_5s_6 - c_1s_2s_4c_5 - s_1c_3s_5s_6 - c_1c_2s_3s_5s_6 - c_1c_2c_3s_4c_6 - s_1s_3s_4c_6 - c_1s_2c_4c_6$$

$$r_{13} = -c_1c_2c_3c_4c_5c_6s_7 + s_1s_3c_4c_5c_6s_7 + c_1s_2s_4c_5c_6 - s_1c_3s_5c_6s_7 + c_1c_2s_3s_5c_6s_7$$

$$-c_1c_2c_3s_4s_6s_7 - s_1s_3s_4s_6s_7 - c_1c_2c_3c_4s_5c_7 - s_1s_3c_4s_5 + c_1s_2s_4s_5c_7 + s_1c_3c_5c_7 - c_1c_2s_3c_5c_7$$

$$r_{21} = s_1c_2c_3c_4c_5c_6c_7 - c_1s_3c_4c_5c_6c_7 - s_1s_2s_4c_5c_6c_7 - s_1c_2s_3s_5c_6c_7 - c_1c_3s_5c_6c_7 + c_2c_3s_4s_6c_7 - c_1s_3s_4s_6c_7 + s_1s_2c_4s_6c_7 - s_1c_2c_3c_4s_5s_7 + c_1s_3c_4s_5s_7 + s_1s_2s_4s_5s_7 - s_1c_2s_3c_5s_7 - c_1c_3c_5s_7$$

$$r_{22} = s_1c_2c_3c_4c_5s_6 - c_1s_3c_4c_5s_6 - s_1s_2s_4c_5s_6 - s_1c_2s_3s_5s_6 - c_1c_3s_5s_6 - s_1c_2c_3s_4c_6 + c_1s_3s_4c_6 - s_1s_2c_4c_6$$

$$r_{23} = -s_1c_2c_3c_4c_5c_6s_7 + c_1s_3c_4c_5c_6s_7 + s_1s_2s_4c_5c_6s_7 + s_1c_2s_3s_5c_6s_7 + c_1c_3s_5c_6s_7 - c_2c_3s_4s_6s_7 + c_1s_3s_4s_6s_7 - s_1s_2c_4s_6s_7 - s_1c_2c_3c_4s_5c_7 + c_1s_3c_4s_5c_7 + s_1s_2s_4s_5c_7 - s_1c_2s_3c_5c_7 - c_1c_3c_5c_7$$

$$r_{31} = s_2c_3c_4c_5c_6c_7 + c_2s_4c_5c_6c_7 - s_2s_3s_5c_6c_7 + s_2c_3s_4s_6c_7 - c_2c_4s_6c_7 - s_2c_3c_4s_5s_7 - c_2s_4s_5s_7 - s_2s_3c_5s_7$$

$$r_{32} = s_2c_3c_4c_5s_6 + c_2s_4c_5s_6 - s_2s_3s_5s_6 - s_2c_3s_4c_6 + c_2c_4c_6$$

$$r_{33} = -s_2c_3c_4c_5c_6s_7 - c_2s_4c_5c_6s_7 + s_2s_3s_5c_6s_7 - s_2c_3s_4s_6s_7 + c_2c_4s_6s_7 - s_2c_3c_4s_5c_7 - c_2s_4s_5c_7 - s_2s_3c_5c_7$$

$$x = c_1c_2c_3s_4l_5 + s_1s_3s_4l_5 + c_1s_2c_4l_5 + c_1s_2l_3$$

$$y = s_1c_2c_3s_4l_5 - c_1s_3s_4l_5 + s_1s_2c_4l_5 + s_1s_2l_3$$

$$z = s_2c_3s_4l_5 - c_2c_4l_5 - c_2l_3$$

4.6.1.2. Inverse Kinematic

After the FK of VHA is completed, the motion of the VHA model is considered based on the inverse kinematics (IK) to solve each joint value in terms of a desired Cartesian position or orientation or both. To derive the IK of the VHA, the following equation (4.50) is computed first based on first four joints:

$$A_0^{4d} = A_0^1A_1^2A_2^3A_3^{4d} = \begin{bmatrix} R_0^4 & p_0^5 \\ 0_3 & 1 \end{bmatrix} \tag{4.50}$$

where

$$R_0^4 = \begin{bmatrix} (c_1c_2c_3 + s_1s_3)c_4 - c_1s_2s_4 & -c_1c_2s_3 + s_1c_3 & (c_1c_2c_3 + s_1s_3)s_4 + c_1s_2c_4 \\ (s_1c_2c_3 - c_1s_3)c_4 - s_1s_2s_4 & -s_1c_2s_3 - c_1c_3 & (s_1c_2c_3 - c_1s_3)s_4 + s_1s_2c_4 \\ s_2c_3c_4 + c_2s_4 & -s_2s_3 & s_2c_3s_4 - c_2c_4 \end{bmatrix} \tag{4.51}$$

$$p_0^5 = \begin{bmatrix} l_5\big((c_1c_2c_3 + s_1s_3)s_4 + c_1s_2c_4\big) + l_3c_1s_2 \\ l_5\big((s_1c_2c_3 - c_1s_3)s_4 + s_1s_2c_4\big) + l_3s_1s_2 \\ l_5(s_2c_3s_4 - c_2c_4) + l_3c_2 \end{bmatrix} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} \tag{4.52}$$

From the equation (4.52), there are four variables on the left hand side, $\theta_1, \theta_2, \theta_3, \theta_4$ with three known values on the right hand side which are x, y and z. From VHA kinematic chain, θ_3 is the shoulder med-lat rotation and therefore, assumed to be fixed at the home position, i.e., $\theta_3 = 90°$. Hence, the equation is reduced to

$$\begin{bmatrix} l_5(s_1s_4 + c_1s_2c_4) + l_3c_1s_2 \\ l_5(-c_1s_4 + s_1s_2c_4) + l_3s_1s_2 \\ -l_5c_2c_4 + l_3c_2 \end{bmatrix} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} \tag{4.53}$$

To find out the rest of the joint angles, θ_1, θ_2 and θ_4, square every element in the matrix and add them together. This will yield

$$l_3^{\,2} + l_5^{\,2} + 2\,l_3l_5c_4 = x^2 + y^2 + z^2 \tag{4.54}$$

From equation (4.54), it can be re-written into the following equation which is the law of cosine.

$$c_4 = \frac{x^2 + y^2 + z^2 - l_3^{\,2} - l_5^{\,2}}{2\,l_3\,l_5} \tag{4.55}$$

Therefore, θ_4 at elbow joint can be found as follow:

$$\theta_4 = tan^{-1}\left(\frac{s_4}{c_4}\right) \tag{4.56}$$

where $s_4 = \sqrt{1 - c_4^{\,2}}$ and the range of motion at elbow joint is limited between (0°, 180°), i.e., $s_4 \geq 0°$. After θ_4 has been found, θ_2 can be calculated from z-component from the equation (4.53). This will give

$$c_2 = -\frac{z}{l_3 + l_5c_4} \tag{4.57}$$

The θ_2 is the shoulder abduction and adduction with maximum range of motion between (-50°, 198°) and hence it can be either $s_2 = -\sqrt{1 - c_2^{\,2}}$ or $s_2 = \sqrt{1 - c_2^{\,2}}$ as follows:

$$\theta_2 = tan^{-1}\left(\pm \frac{\sqrt{1 - c_2{}^2}}{c_2} \right) \tag{4.58}$$

After θ_2 and θ_4 have been solved, θ_1 can be calculated by means of x and y components from equation (4.53) and this will yield

$$\begin{bmatrix} s_4 l_5 & s_2 c_4 l_5 + l_3 s_2 \\ s_2 c_4 l_5 + l_3 s_2 & - s_4 l_5 \end{bmatrix} \begin{bmatrix} s_1 \\ c_1 \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} \tag{4.59}$$

From equation (4.59), s_1 and c_1 can be solved and after solving both, θ_1 can be determined by

$$\theta_1 = tan^{-1}\left(\pm \frac{\sqrt{1 - c_1{}^2}}{c_1} \right) \tag{4.60}$$

There are two possible values for θ_1 as well due to the shoulder flexion and extension range of motion which is within (-61°, 188°). After shoulder orientation and elbow joint angle have been determined, the next step is to find the wrist orientation of the VHA model and this is done based on further derivation as in the following equations:

$$R_4^7 = R_4^0 R_0^7 = (R_0^4)^T R_0^7 = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} \tag{4.61}$$

$$R_4^7 = R_4^5 R_5^6 R_6^7 = \begin{bmatrix} c_5 c_6 c_7 - s_5 s_7 & c_5 s_6 & - c_5 c_6 s_7 - s_5 c_7 \\ s_5 c_6 c_7 + c_5 s_7 & s_5 s_6 & - s_5 c_6 s_7 + c_5 c_7 \\ s_6 c_7 & - c_6 & - s_6 s_7 \end{bmatrix} \tag{4.62}$$

From above equations $c_6 = -r_{32}$ with wrist flexion and extension range of motion at (-81, 90) and therefore θ_6 can be calculated based on equation (4.63).

$$\theta_6 = tan^{-1}\left(\pm \frac{\sqrt{1 - r_{32}{}^2}}{(-r_{32})} \right) \tag{4.63}$$

From equation (4.61& 4.62), θ_5 can be found from r_{12} and r_{22} as follows:

$$\theta_5 = tan^{-1}\left(\pm \left(\frac{r_{22}}{r_{12}} \right) \right) \tag{4.64}$$

Similarly, θ_7 can be found from r_{31} and r_{33} as follows:

$$\theta_7 = tan^{-1}\left(\pm\left(-\frac{r_{33}}{r_{31}}\right)\right) \tag{4.65}$$

After finding all the joint angles as discussed above, the next step is to create the 3D virtual model of the arm and this is discussed in the following Section 4.5.2.

4.6.2. Virtual Human Arm Model

The model of VHA is developed in a 3D Blender which consists of 18 segments: each segment at upper arm, forearm and palm, three segments at thumb: metacarpals, proximal phalanges and distal phalanges, and three segments each for the rest of the fingers: proximal phalanges, intermediate phalanges and distal phalanges as shown in Figure 4.19. From the figure, the orange dot represents the joint between each segment and there are a total of 18 joints. In the developed VHA model, there are 3DOFs at shoulder joint, 1DOFs at elbow joint, 3DOFs at wrist joint, 5 DOFs at the thumb and 4DOFs each for the rest of the fingers with a total of 28DOFs in the construction. However, in this thesis, only shoulder joint articulations are considered for upper limb rehabilitation. After defining the segments and joints in the Blender for VHA model, the arm structure is constructed based on the parent-child arrangement. This is completed by rearranging the note tree so that parent link pointed to the child link, i.e., the upper arm is the parent link to the forearm child link and the forearm is the parent link to the wrist child link and so on to the end link; the last link of the finger digits. The digits are arranged in such a way that they are brother links as they had the same parent link. Each finger is separated into three parts: the distal, intermediate and proximal phalanges with the thumb having distal, proximal phalanges and

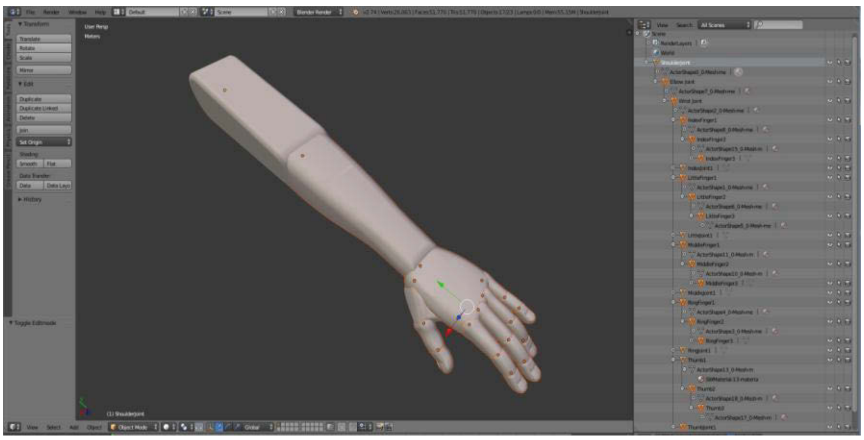


Figure 4-19: Hierarchy structure of Virtual Human Arm Model

metacarpals. They are rearranged so that the proximal phalange is the parent to the intermediate phalange child link which is parent to the distal child link. As for the thumb, the metacarpal is the parent to the proximal phalange child link which is parent to the distal child link. This parent-child relationship is incorporated to ensure any motion of the parent link will have an effect on the child links during simulation. After all the segments and joints are properly defined in the Blender, the model is exported as collada (.dae) format to maneuver in Flash CS6. From Flash CS6, the model is imported via Papervision3D (PV3D) which is an open source, 3D graphics engine for Flash platform [173]. The 3D model is then loaded in .dae format for all the segments and joints with default colour and then rendered on the computer screen. The fragments of code that are responsible for VHA model loading and skin color updating in Flash are defined in Appendix A2.

4.6.3. Experiment and Results

In order to evaluate the performance of VHA, two types of experiment were conducted. The results from the experiments had been published in [244]. The experiments included *Manual Articulations and FK & IK Articulations. Manual Articulation* was to make sure that the links, joint angles and parent-child relationships were properly assigned to the model. After confirming the *Manual Articulation*, the model was imported into Flash Platform to validate the model articulations with developed *FK* and *IK* algorithm in both random trajectory data and CMR exercise trajectory data.

4.6.3.1. Manual Articulation

To verify the arm structure, the rotation of each joint was tested manually by specifying the particular angle value at each and every joint in both Blender and in Flash as shown in Figure 4.20 and Figure 4.21. It was found that the parent-child links at every joint level were properly defined and it was able to rotate as desired orientation at desired joint level. During this testing, the ROM constraints of the model were not defined to mimic the real arm articulations and it was only defined during *FK and IK articulations*. Although the finger articulations were not used in ARIS at this time, they were tested and catered for future manipulations, for instance hand rehabilitation.

4.6.3.2. FK and IK Articulation

After confirming the segments, joints and their connections of VHA model, it was tested for *FK and IK articulations*. First of all, the difference between Flash coordinate system

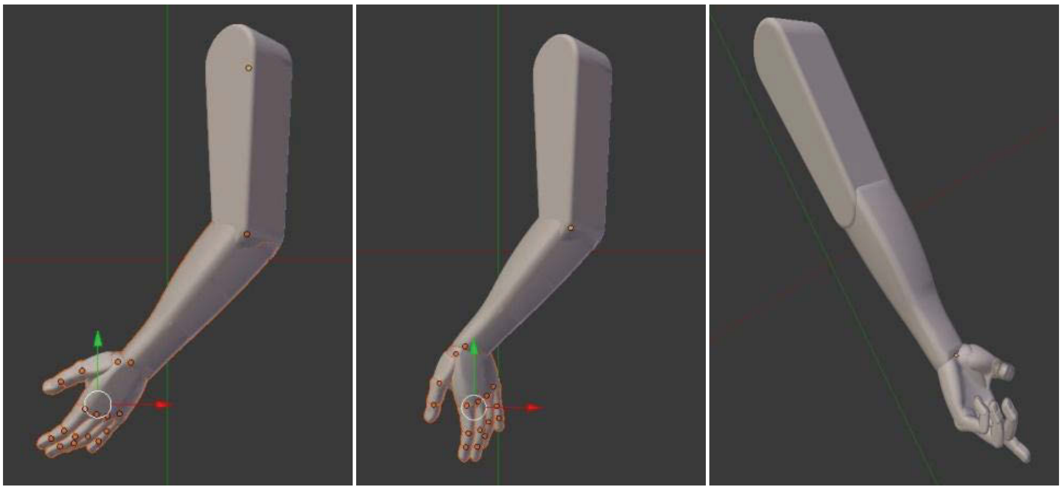


Figure 4-20: *Manual Articulation* of VHA model at different positions and orientations in Blender

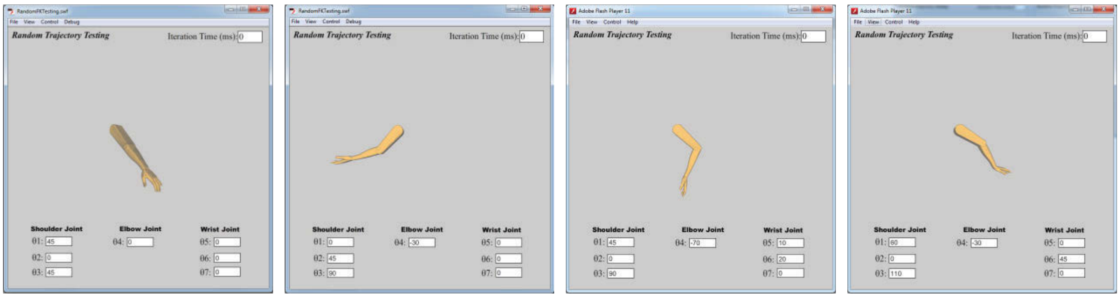


Figure 4-21: *Manual Articulation* of VHA model at different positions and orientations in Flash Professional CS6

and model coordinate system were studied to ensure the imported model was located in correct orientation and position in Flash platform. In Flash, the origin or the registration point is located at the corner of the top left point of the stage, +*y* is pointing downward unlike in Cartesian coordinate space in which the *y*-axis is increasing "up" while +*x* is pointing towards the right and +*z* is into the paper and as for the imported model coordinates, +*x* is pointing towards right, +*y* is pointing up and +*z* is into the paper which are shown in Figure 4.22.

After the model had successfully rearranged the coordinates, developed *FK* and *IK* algorithms were tested. Initially, *Prediction Mode* or *FK* was tested where the joint angles were given in the model randomly followed by the joint angles for CMR exercise. In *Prediction Mode*, the joint angles were achieved by prediction model which is proposed in section 4.4. These joint angles were then sent to *FK* algorithm and drive the VHA model. The actual hand locations were evaluated by comparing with desired hand positions and

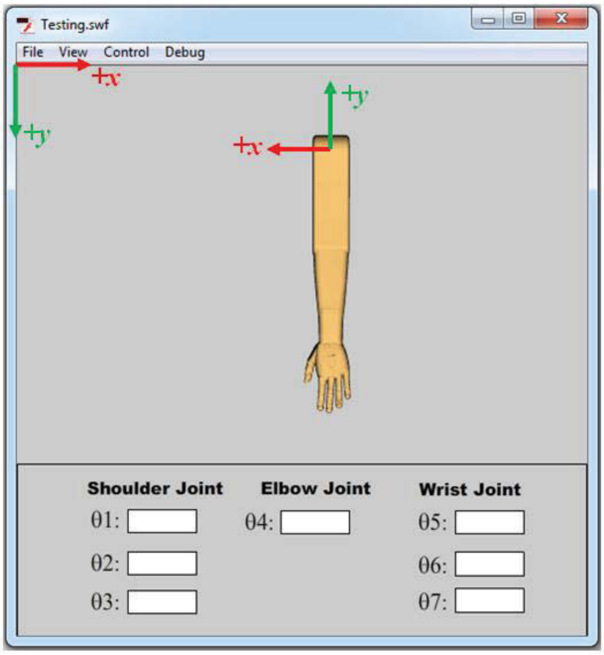


Figure 4-22: Coordinate space of game stage in Flash and VHA model

part of the results are shown in Table 4.5 and Table 4.6. From the trajectory results, it was found that the end-effector error is less than 1.32 mm which is within the allowance of collision detection to perform pick and place actions in the exercise. The computational time for simulation was also very fast as it was completed within 0-1ms per iteration. The results from the graphical simulations of the VHA model in *Prediction Mode* are as portrayed in Figure 4.23.

Table 4.5: Iteration time and norm error results from random trajectory motion in *Prediction Mode* with θ1 vary from 45° to 55° and θ2 vary from 30° to 40° while the rest of the angles remain at 0°

θ_1(°)	θ_2(°)	‖e‖ in mm	Iteration Time (ms)
45	30	0.3976	0
46	31	0.3981	0
47	32	0.4052	0
48	33	0.4134	0
49	34	0.4289	0
50	35	0.4296	0
51	36	0.4311	0

θ_1(°)	θ_2(°)	||e|| in mm	Iteration Time (ms)
52	37	0.4332	0
53	38	0.4367	1
54	39	0.4382	0
55	40	0.4386	0

Table 4.6: Iteration time and norm error results from CMR exercise in *Prediction Mode* with θ2 vary from -80° to -90° and θ3 vary from 80° to 90° while the rest of the angles remain at 0°

θ_2(°)	θ_3(°)	||e|| in mm	Iteration Time (ms)
-80	80	0.2443	0
-81	81	0.252	1
-82	82	0.26	0
-83	83	0.2884	0
-84	84	0.2953	0
-85	85	0.3028	1
-86	86	0.3154	0
-87	87	0.3231	0
-88	88	0.3469	0
-89	89	0.3623	0
-90	90	0.37	0

After *Prediction Mode* had been tested, *Threshold Mode* or *IK* algorithm was tested by

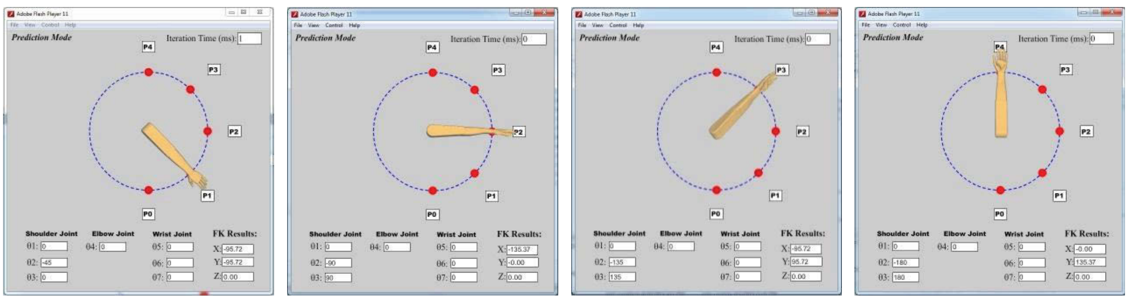


Figure 4-23: Graphical simulation of *Prediction Mode* in CMR exercise

experiments in both random positions and CMR exercise positions. In the *Threshold Mode,* the desired hand positions were given in terms of X, Y and Z coordinates and the required joint angles were calculated by *IK* algorithm to simulate VHA model. In the case of random positions, the experiment was carried out with variation of Y values while both X values and Z values were fixed at zero. Similar to the *Prediction Mode*, the error-norm of the joint angles and iteration duration were calculated and the results of Y values from -70mm to -60mm are as shown in Table 4.7. In the experiment of CMR exercise positions, the values were calculated for X and Y while Z values were fixed at zero. The calculated results of X values from -100mm to -110mm are tabulated in Table 4.8. From the results of *Threshold Mode*, the error-norm values were less than 1° and hence, the calculated joint angles are sufficiently accurate as desired joint angles that mimic the human arm articulation. The graphical simulations of VHA articulations in *Threshold Mode* are portrayed in Figure 4.24.

Table 4.7: Iteration time and norm error results of random motion in *Threshold Mode* with Y-axis vary from -70mm to -60 mm while X and Z remains at zero

Y(mm)	||e|| in degree	Iteration Time (ms)
-70	0.4386	0
-69	0.4382	0
-68	0.4367	1
-67	0.4332	0
-66	0.4311	0
-65	0.4296	1
-64	0.4289	0
-63	0.4134	0
-62	0.4052	0
-61	0.3981	1
-60	0.3845	0

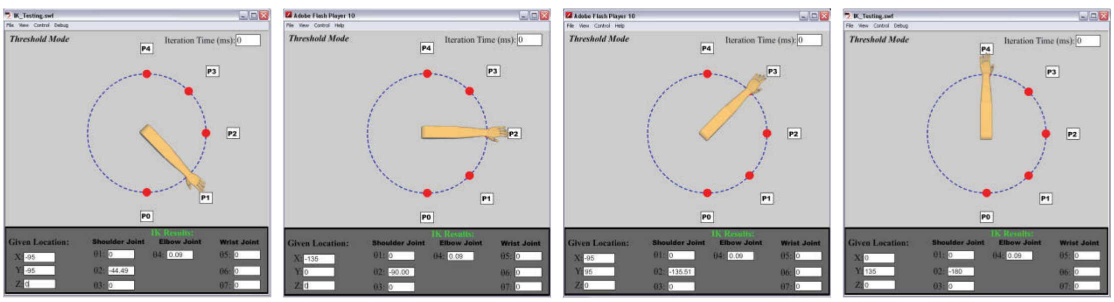


Figure 4-24: Graphical simulation of *Threshold Mode* in CMR exercise

Table 4.8: Iteration time and norm error results of CMR motions in *Threshold Mode* with X-axis vary from -100mm to -110 mm, Y-axis vary from -90mm to -80mm while Z remains at zero

X(mm)	Y(mm)	||e|| in degree	Iteration Time (ms)
-100	-90	0.3863	0
-101	-89	0.3673	1
-102	-88	0.3593	0
-103	-87	0.3529	0
-104	-86	0.3462	0
-105	-85	0.317	1
-106	-84	0.2693	0
-107	-83	0.2371	0
-108	-82	0.2183	0
-109	-81	0.1952	0
-110	-80	0.1773	0

After the experiments of VHA model had been conducted and verified, Augmented Reality-based Illusion System (ARIS) for upper rehabilitation system was developed in which VHA model is employed to perform as a real arm. The details of the developments of the system and experiments are explained in the following chapter.

4.7. Chapter Summary

In this chapter, the second and third contribution of the thesis is discussed. Firstly, a neural-muscle activation model was proposed to find the actual muscle activation level during the performance of the task by considering the best parameters for the model. The proposed model was then compared with the traditional time-domain feature extraction method to show its effectiveness. Secondly, two joint angle prediction models based on BPNN and ELM were proposed in both offline and online modes. The comparisons were performed between these two prediction models in both offline and online mode. From the experiment results, it was found that the proposed NMA model with ELM provided the best accuracy with better computational cost. Hence, this model was chosen as an optimal controller to control the VHA model in real time. Finally, the development of the VHA model was detailed in this chapter. The experiments on VHA model simulation were also performed with both manual and chosen optimal controller. The results from the experiments showed that real time biosignal driven VHA model had successfully acquired data, processed data and simulated the model in less than 40ms which the user perceived as a real time simulation of the VHA model.

Chapter 5
Illusion based Upper Limb Rehabilitation System

5.1. Introduction

Neural plasticity is the ability to compensate for loss of function and reorganize the nervous system to make other parts of the CNS take over some of the functions that were lost from the destruction of neural tissue due to any neurological disorders. Therefore, this is the most important function to stimulate in order to restore the lost functions in the context of rehabilitation. To exhibit the neural plasticity, learning is the most important matter because learning can produce changes in synapses, neurons, and neuronal networks within specific brain regions. Through learning, the brain will encode new experiences and enable behavioral change [245]. Taking advantage of neural plasticity, there is overwhelming evidence of increase in motor cortex excitability which significantly improves dexterity depending on motor experiences such as forced-use therapy [246], constraint-induced movement therapy (CIMT) [49] and bilateral movement therapy [247]. However, most of these interventions are labor intensive due to one-to-one attention and a manual approach between patient and therapist throughout the rehabilitation period. Moreover, the therapeutic effects are diminished for those who suffer from severe impairment as they are reluctant to perform physical exercise. In order to close this gap, mirror therapy (MT) is introduced in rehabilitation therapy as this is a patient-oriented therapeutic intervention that focuses on intact limbs by means of visual illusion via a conventional mirror. The studies have reported that the effects of MT on the upper limb rehabilitation are improved in terms of ROM, increased muscle strength, improvement in speed and accuracy of the movements and enhancement in motor recovery and self-care ability [48, 248, 249]. Although there is overwhelming evidence of MT providing motor recovery, it is not adequate to provide as a novel rehabilitation system as there are several aspects that still need to be addressed. These include limitations on type of movements, only available on certain parts of the limb to rehabilitate, mundane physical exercise and absence of biological feedback that motivate the patient in long term engagement.

This chapter is oriented toward the development of an Augmented Reality-based Illusion System (ARIS) based on the concept of MT on upper limb rehabilitation. This is driven by the fact that there is a lack of integration of all the possible aspects that enhance motor recovery in current upper limb rehabilitation systems. Hence, ARIS is proposed to close the gaps by integrating together AR environment, biofeedback and motivated therapeutic exercises that lead to induce neural plasticity change. In order to proceed with the development of a novel rehabilitation system, ARIS, an introduction to MT in upper limb rehabilitation will be given first followed by how to integrate visual illusion or mirror visual feedback (MVF) to provide "Fool-the-Brain" concept.

5.2. Mirror Therapy in Upper Limb Rehabilitation

Mirror Therapy (MT) is a drug free treatment that is used to provide MVF by utilizing mirrors to trick patients' brains into thinking that they were moving their hand or limb. In order to perform the MT, a mirror box was developed which consists of an optical mirror placed vertically in the middle of the box without a roof with two holes in front as shown in Figure 5.1. The patient's hands are inserted in the box through these two holes where the mirror is faced the healthy limb. The patient is then requested to view the reflection of the

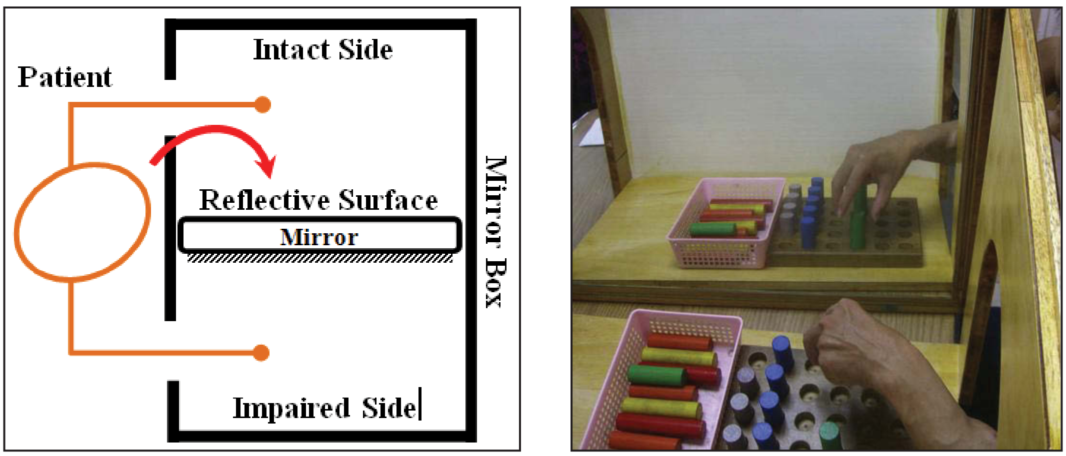


Figure 5-1: Schematic diagram of MT (left) and actual MT box (right)

normal hand in the mirror to create the illusion of observing two hands, when in fact the patient is only seeing the mirror reflection of the intact hand. It was introduced in 1996 by Ramachandran and Roger –Ramachandran [250] to treat phantom limb pain after amputation and since then it has been applied in several fields such as stroke rehabilitation [195], phantom limb pain [251], complex regional pain syndrome [252], limb rehabilitation [253] and neuropathic pain [254].

In the context of limb rehabilitation, MT is widely employed to restore the normal limb functions via graded exercises with a conventional mirror box and the positive effect of visual feedback in the form of bilateral symmetrical movements have been reported. However, it was found that these movements do not affect the coordination movement of both upper limbs[255]. In addition to this, different neural networks in the brain might be engaged when looking at oneself in a mirror compared to when one looks at oneself directly [256] and the experimental manipulations are rather constrained with the use of the mirror box to test the precise nature of observed effects. To overcome these limitations, VR and AR environments are introduced to extend the use of mirror visual feedback which enhances motor recovery through neural plasticity. To investigate this idea, Dong Jin Lee and his research group has developed the virtual reality reflection system to mimic the conventional MT concept in VR environment [257]. With the aid of VR environment, the limitations of bilateral symmetrical movements are overcome and an asymmetric training program was introduced and studied on the effect on hand function. The study has confirmed that the repeated asymmetrical movements with both hands are more effective than symmetrical movements and improved the spatially coupled motion. Another study based on AR environment was performed by [258]. They have developed the augmented reflection technology (ART) system which consists of augmented mirror boxes and two display screens. The ART system mimics the MT by mirroring the real hand in the box, i.e., flipping in the horizontal direction, displaying on the computer screen on real hand and flipped hand, and manipulating the hand therapeutic game. Although the system has provided promising results, the requirements of hardware setups, total immersion of forearm and hand in the enclosed box and manipulation in that box, lack of biofeedback in the system could lead to a less effective rehabilitation system.

In the context of MT in VR and AR environment, the ownership of the virtual arm or artificial arm that is created in VR and AR environment plays a vital role for the user to perceive this virtual arm or artificial arm as one of his/her own arms; this is termed the

"Fool-the-Brain" concept. This is to replace the reflected arm by a conventional mirror and create the MVF in VR and AR environment. The detailed concept of "ownership" feeling and research on the perception of ownership illusion is described in the next section.

5.2.1. Ownership Illusion

Ownership illusion is to perceive the ownership of virtual or artificial limbs as one of the body parts in either real world or virtual world. In the context of rehabilitation, this is one of the important factors to stimulate neural plasticity during motor recovery stage. In order to measure the feeling of ownership illusion, the rubber hand illusion (RHI) was first introduced by Botvinick and Cohen [259] in 1998. In contrast to MT, RHI was experimented by placing the actual human arm size rubber hand next to the participant's occluded hand. In their work, two types of measurements were conducted to evaluate the effect of ownership. First, rubber hand and occluded hand were stroked synchronously to evoke the proprioceptive feeling of the own hand and the questionnaire results found that the ownership illusion was perceived when the stroking was synchronous. In the second experiment, the displacement of participant's left index finger was measured by an inter-manual reaching task in the darkness. It was found that the movement occurred during the synchronous stimulation. This displacement effect was termed the "proprioceptive drift" which interacts between vision, touch and proprioception [260] and the study concluded that the feeling of ownership is correlated with the proprioceptive drift. Several similar works had also demonstrated the ownership illusion with rubber hand and proven with positive results by measuring the ownership effect via stimulation in synchronous actions [261] as well as in proprioceptive drift [259, 262, 263]. Another type of ownership measurement can be made by evaluating skin-conductance response (SCR) where SCR is a measurement of ownership that reflects fear and anxiety when the owned body part is under physical threat; for instance, the artificial arm is stabbed by a knife [264]. This approach had been experimented on [265] and his results had shown that there was a significant response when the rubber hand was in threat immediately after the synchronous condition. This showed that the participants' perceptual and emotional systems treated the rubber hand as part of their bodies. In addition to rubber hand experiments, similar experiments were conducted with VR setup in VR environment. In the work of Hagni et al.,[258] , the virtual forearm and hand were developed in VR environment and the ownership feeling was evaluated by creating the scenario in such a way that the virtual arm was threatened. Their results also showed that virtual visual feedback together with mental imagery may induce the ownership perception as part of the body. Additional investigations into virtual hand illusion were carried out by Raz et al. [266]. From their experiments, it was found that there was a strong sense of perception of ownership during the synchronous conditions when both the real hand and virtual hand moved at the same time. In addition, they also found that the addition of haptic feedback to both real and virtual hand provided greater sense of ownership perception.

Overall, the literature suggests that there is considerable potential to fool our perceptions by considering the factors as follows and develop the perception of ownership of the artificial arm as part of the body.

- The illusion is stronger and more prevalent when single arm is presented to user. Therefore, it is important to hide the real arm from the user's point of view when importing the artificial arm to the user.
- The artificial arm must be replaced at the site of the real arm as close as possible so that it resembles the user's own arm.
- The stimulation must be applied to both artificial and real arm synchronously to get the experience that artificial arm belonged to user's body.
- The articulation of artificial arm and real arm must be in an identical way with the real arm ROM.

5.2.2. Limitation of Existing MT Rehabilitation System

To be able to provide a novel rehabilitation system, it is necessary to integrate different aspects of manipulative controls that maximize both physical and mental recovery as well as to provide an affordable and convenient system to the patient. Although numerous MT rehabilitation systems for upper limb had developed to enhance upper limb motor recovery, such novel systems are very limited not only due to lack of one or more features such as effective visual feedback that induce brain plasticity to enhance the fast motor recovery and motivation but also the requirements of hardware apparatus.

In the context of traditional MT rehabilitation, although a low cost conventional mirror is required to perform the upper limb exercise, only up to the elbow joint can be placed in the mirror box and hence only hand and forearm are reflected from the mirror during rehabilitation process. In addition to this, the placement of the mirror between the intact and impaired arm leads to limit the ROM in elbow articulation especially in horizontal movements. To overcome these limitations, VR was introduced for MT system by creating the virtual arm to mimic the idea of mirror reflection. Although the limited ROM issue is solved by manipulating of virtual arm model in VR environment, the requirements of additional communication devices and full immersion in VR environment are still major issues to the patient. In addition, the feeling of ownership of the virtual arm has come into the picture so that virtual arm in VR mimics exactly the physiological concept behind MT. However, up to date existing MT systems that are proposed through VR environment are still lacking in biofeedback which is one of the most important features in the rehabilitation field, employing of the patient's own biosignal to enhance the stimulating of neural plasticity as well as the motivational therapeutic exercises as a physical therapy.

In an attempt to close this gap, a novel AR based illusion system (ARIS) is proposed. The proposed system is developed by employing the virtual human arm (VHA) that was developed in Chapter 4 to induce ownership perception in AR environment and integrating the AR based therapeutic exercises with a richness of immediate audio and visual feedback. Two types of EMG biofeedback mode are employed to stimulate the ownership illusion (1) *Prediction Mode*: self biosignal to predict the joint angle in real time to drive the VHA in synchronous motion with real arm to perform therapeutic exercise, (2) *Threshold Mode:* compare the measured EMG signals from real arm with predefined value to drive VHA model to perform exercise. These contributions are presented in the following sections.

5.3. Thesis Contribution-4: Augmented Reality-based Illusion System (ARIS)

The fourth contribution in this thesis is the development of Augmented Reality-based Illusion System (ARIS) which adapts the MT concept to perceive artificial visual feedback to improve impaired arm movements by taking advantage of human brain plasticity nature. This work had been published in [267]. In contrast to conventional MT, ARIS only requires a PC with a cheap webcam and any colour as a marker to track the motion of the arm. ARIS aims not only to provide recovery from physical activities but also to stimulate neural plasticity in an effective way. To fulfill such ambitious objectives, several fields are combined under one roof of ARIS such as AR technology, computer vision, virtual modeling and machine learning. Employing of AR technology in ARIS aims to motivate the patients' willpower to perform the long term rehabilitation therapy. In addition to AR technology, EMG biosignal is employed in ARIS to detect the intention of the user to manipulate the VHA in ARIS. User intention is detected based on EMG threshold level according to the continuous prediction algorithm developed in Chapter 4. The main framework of ARIS is developed in Adobe Flash Professional CS6 platform while collection of EMG data and detection of EMG threshold is developed in the Matlab platform. The schematic diagram of the ARIS is illustrated in Figure 5.2. ARIS is comprised of several modules namely database module, illusion environment module, multiple colour tracking module, therapeutic exercise module and real-time data acquisition module.

5.3.1. Database Module

Database module in ARIS is similar to the RehaBio system which stores the patients' data and training information. The information includes patient's particulars, maximum EMG threshold value at the beginning of the training, the coordinates of the real arm trajectory at the initial stage as well as the maximum angle at shoulder or elbow joint. These are important data to evaluate the performance of patient improvement along the training period. The initial data will be collected and saved in the database module before the very first therapy session by manual entry. After that all the necessary data will be automatically saved at the end of every therapy session. This will look for the EMG threshold value from

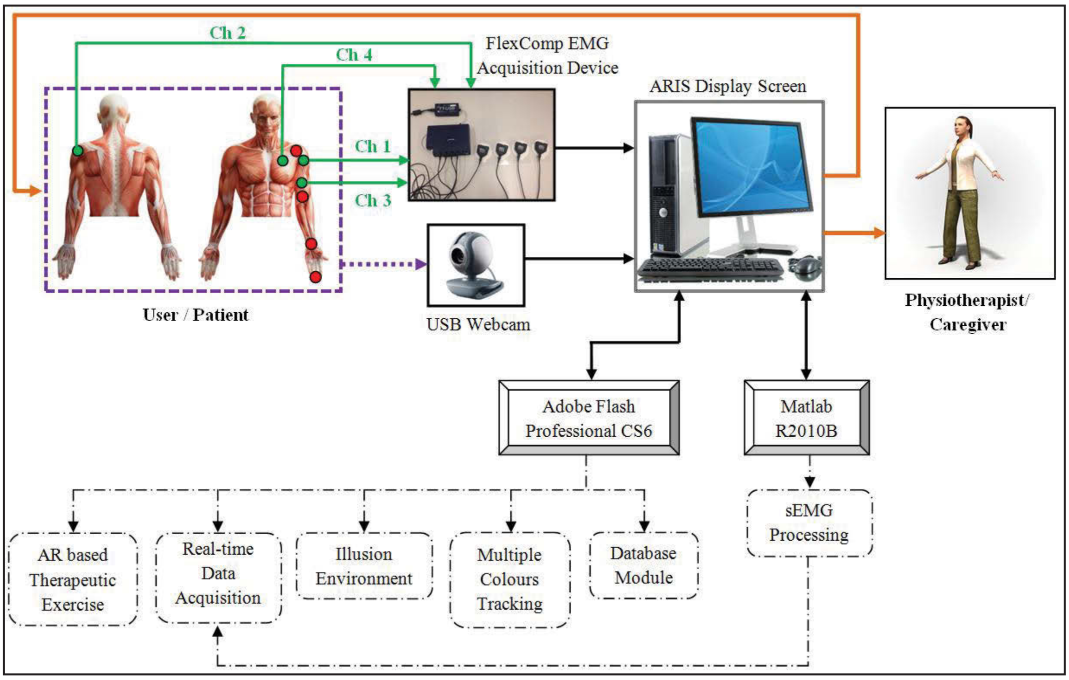


Figure 5-2: System Architecture of the ARIS, red dot represents the location of colour markers and green dot represents the site of electrodes

real-time data acquisition module, save all the x, y and z coordinates of the hand marker trajectory from multiple colours tracking module and take all the joint angle data from illusion environment module and send the information into database module as shown in the block diagram, Figure 5.3. All of these data will be the reference data for the next training session which will be loaded automatically in ARIS according to the particular patient.

5.3.2. Multiple Colour Tracking Module

In ARIS, four colour markers are attached to identify the current location of the real arm joints: shoulder, elbow, wrist and fingertip (Figure 5.2) in every frame by means of a single webcam. Based on the single tracking algorithm that was proposed in Chapter 3, multicolour tracking algorithm is implemented as portrayed in Figure 5.4. The colour marker at each joint is defined by user one by one. The selected colour pixels are then stored in separate classes to calculate the new pixels to track in every frame that is captured by webcam. After successful tracking of every colour, width and height of the real arm is calculated. The width of the real arm is extracted by the width of the colour marker whereas the length of the real arm is calculated by Pythagoras's Theorem based on the absolute values of coordinates between colour markers. The calculated dimensions of the real arm are used to create the coverage object for artificial visual illusion in illusion

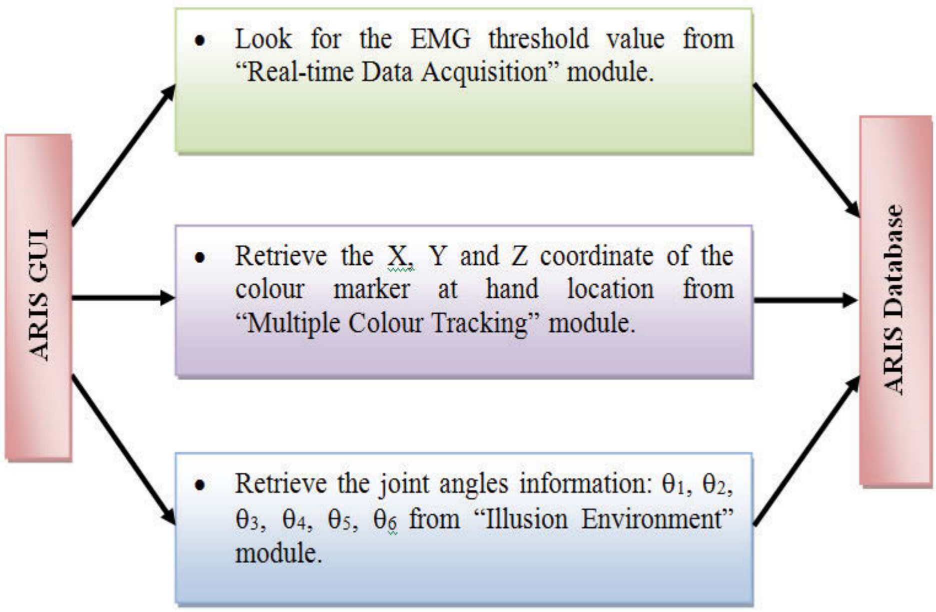


Figure 5-3: Database Module in ARIS

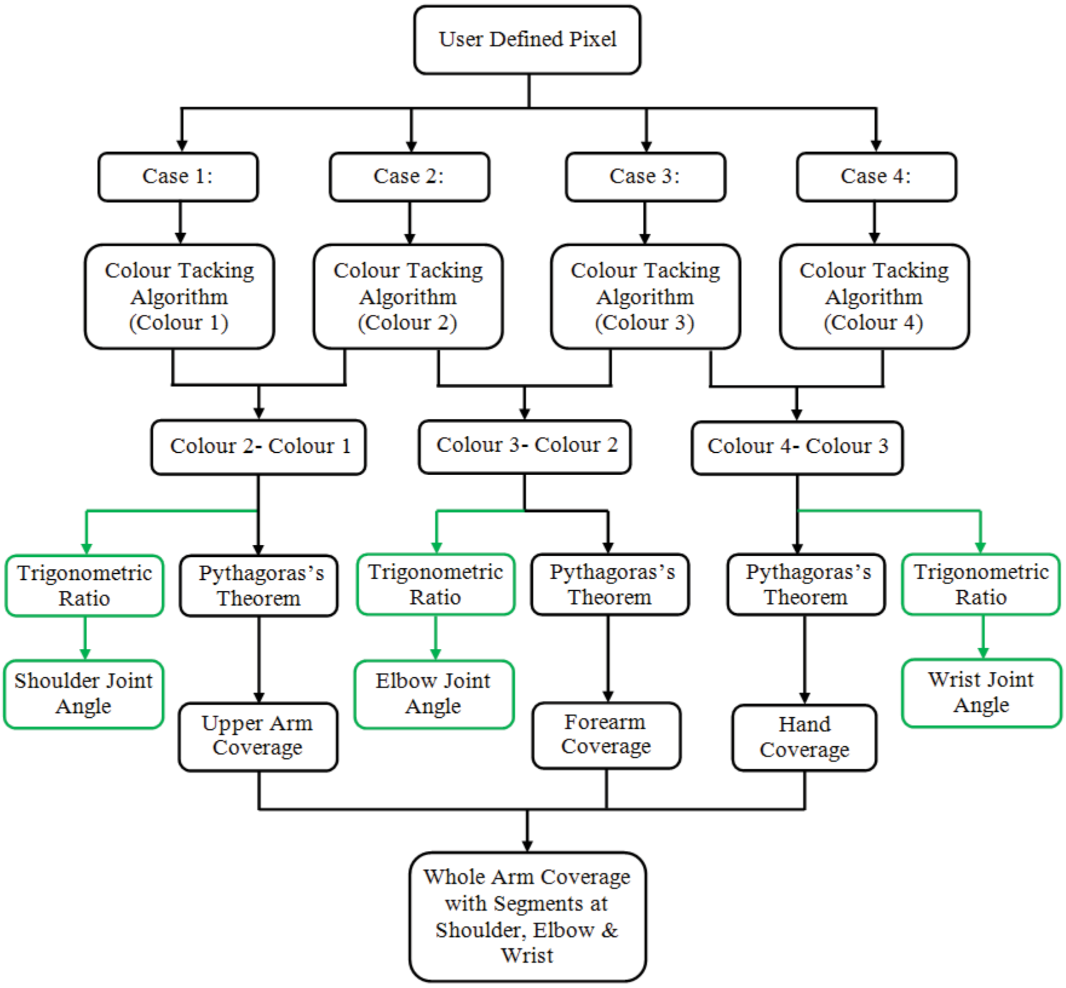


Figure 5-4: Architecture of Multicolour Tracking Module

environment which will be explained in detail in the next Section 5.3.3. At the same time, shoulder, elbow and wrist joint angles of the real arm are also calculated by Trigonometric Ratios and stored in the system. This is to detect the real arm joint angles without the need of any inertial measurement unit (IMU) device. Once the coverage properties are defined, they are attached to the respective joint such as upper arm coverage attaches between shoulder and elbow joint, forearm coverage attaches between elbow and wrist joint and the hand coverage attaches between wrist and fingertip. These attachments of the coverage are perceived by user as hiding the real arm in every frame on the display screen.

5.3.3. Illusion Environment Module

The idea of this module is to create the visual illusion environment to the user/patient by hiding the real arm and importing the virtual arm seamlessly. This is done by overlaying the VHA model on top of the real impaired arm with the aid of multicolour tracking module. From multicolour tracking module, the current location of the shoulder joint, elbow joint, wrist joint and fingertip are defined and this is where removal of real arm segments and attachment of VHA model taken place. The overlaid model, VHA will allow the user to perceive as his/her own arm on the display screen. To create such illusion environment, four layers are developed and each layer responsibility is depicted in Figure 5.5. The very first layer is fed with live video via webcam to create AR environment. In the second layer, three coverage objects are developed based on the width and height of the user's upper arm, forearm and hand captured by webcam as explained in Section 5.3.2. The

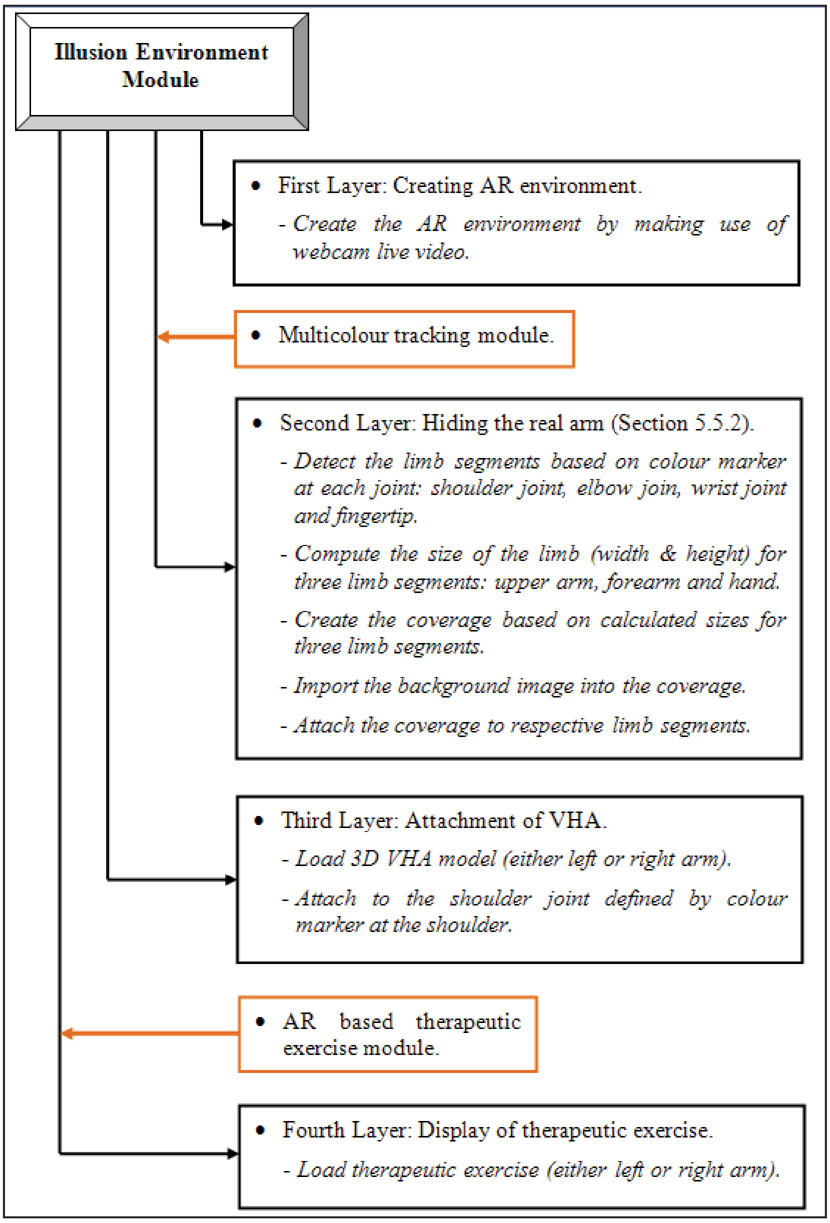


Figure 5-5: Flowchart of Illusion Environment Module

inner area of the coverage objects are imported with webcam captured AR background from AR environment so that this will appear as removing of the real arm from the display screen.

The placement of the coverage objects are based on the current location of the colour marker at shoulder, elbow and wrist joint so that real arm will always overlap with coverage objects wherever user's arm moves. In the third layer, VHA will be attached at the shoulder joint marker and overlaid on top of the coverage objects to create the illusion scene of the real arm. The rendering of the VHA is completed in Flash platform with 3D graphics engine named Papervision3D. To visualize as close as possible to the real arm of the user, the skin colour of the VHA mimics the skin colour of the real arm by selecting the user's skin colour on the display screen. The selected skin colour pixel from webcam is then processed with colour tracking algorithm to coat the selected colour on the VHA model. One of the VHA functions in AIRS is to induce the ownership illusion and when user cannot accomplish the required task due to his/her limited motor movement, it will take over the job of the real arm as if user is still performing the reaching task. This appearance on the screen will fool the user scene that he/she is still able to perform the reaching exercise by his/her own effort to the destination point. The detailed functions of VHA in ARIS will be further discussed in section 5.3.4. In the fourth layer, the AR based upper limb therapeutic exercise is loaded to perform the rehabilitation therapy. The

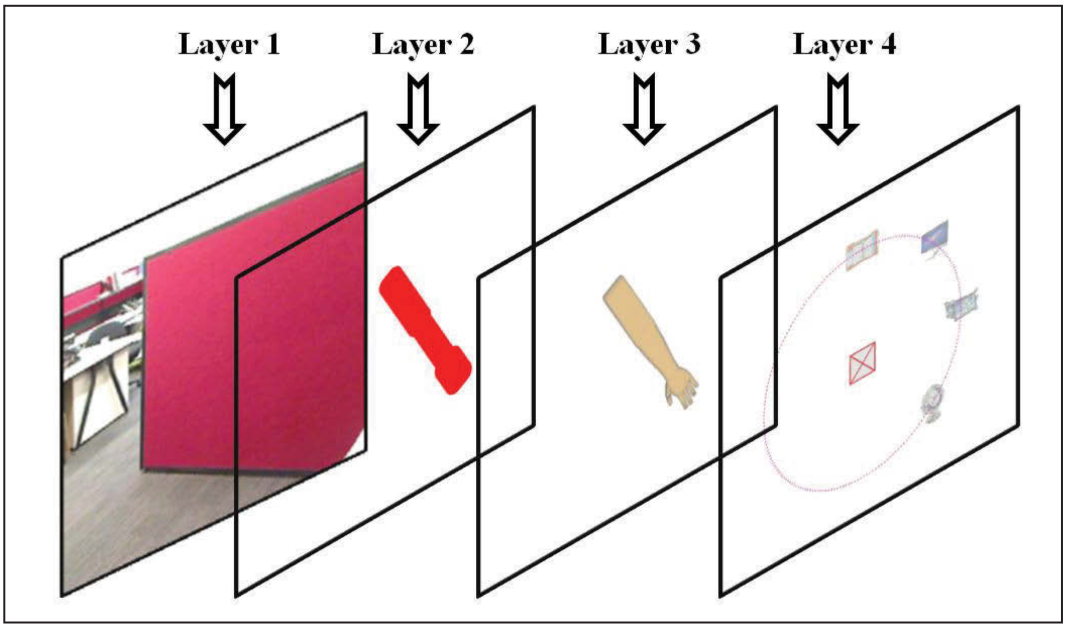


Figure 5-6: Graphical representation of illusion environment module

graphical presentation of each layer is portrayed in Figure 5.6.

5.3.4. Real-time Data Acquisition Module

There is overwhelming clinical evidence that by the integration of biological signal in rehabilitation enhances motor recovery [20]. The employment of EMG signals is one of the most important ingredients to provide an efficient upper limb rehabilitation system. Therefore, the data acquisition module in ARIS is developed in order to compare the user defined data with real-time data from processed signals or predict the user intention from his/her latent biological signal which is EMG signal, at the same time it also serves as a biofeedback to the user to promote the recovery from lost functions effectively. The concept behind data acquisition module is illustrated in Figure 5.7. This is the module in which two platforms communicate through universal datagram protocol (UDP) communication by setting up the internet protocol (IP) and port information for both sender (Matlab) and receiver (CS6). In Matlab platform, the EMG signals are recorded via FlexComp device and processed to remove noise and extract the muscle activation level or threshold level. The processed signals are then computed to predict the joint angles by the proposed algorithm which is the continuous joint angle prediction in Chapter 4. In CS6 platform, there are two options to simulate the VHA model; threshold mode or prediction

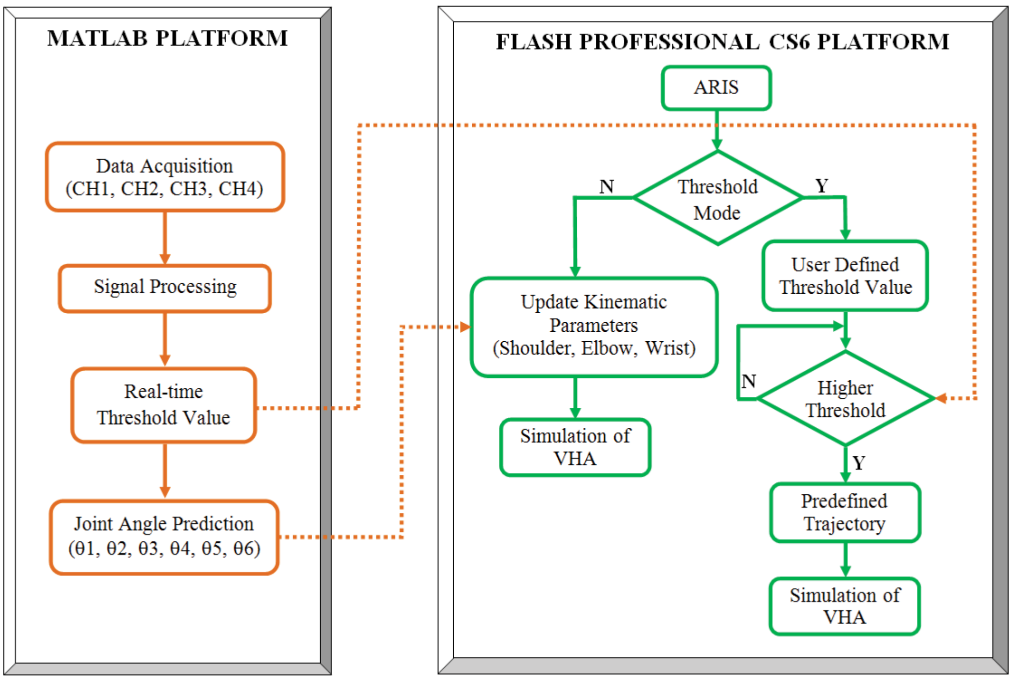


Figure 5-7: The concept of data transfer from Matlab platform to CS6 platform in real-time via UDP communication represented by dashed arrows

mode. Threshold mode works by comparing the real-time data sent from Matlab at the level of real-time threshold value and user defined threshold value from ARIS GUI. If real-time data is above the defined threshold value, predefined trajectory data of chosen exercise will be loaded and these data will drive the VHA model. This threshold mode is aiming for those who have a severe impairment and hence the simulation of VHA (artificial visual feedback) performs automatically. In prediction mode, the predicted joint angles calculated from processed EMG signals are imported to CS6 platform in real-time via universal datagram protocol (UDP) communication to update the respective kinematic data in VHA model. By updating the kinematic data, the pose of VHA model will be refreshed and the simulation of VHA in illusion environment will be visualized. In ARIS, the calculations for angle prediction, transferring data, updating of the kinematic data and refreshing for new pose of VHA are completed in less than 40ms which is required for resemblance of smooth and life-like articulation [152]. The prediction mode is aiming for both mild and recovery stage impairment. For mild stage impairment, predicted VHA simulation and real arm work simultaneously to complete the chosen therapeutic exercise. As for recovery stage, most of the movements in the exercise will be completed by the real arm and the predicted simulation will take over the job that the real arm cannot achieve.

5.3.5. Therapeutic Exercise Module

The available therapeutic exercises in ARIS are PPR and CMR which were described in Chapter 3. The predefined trajectory is necessary in ARIS for *Threshold Mode* for those who suffer from severe impairments with very limited upper limb movement. The exercise and rehabilitation aims of each exercise are also detailed in Chapter 3. In addition to the exercise development, the calibration stage is added to every exercise in ARIS. The purpose of calibration stage in ARIS is defining the exercise area by detecting the maximum range of motion that user is able to reach in terms of X-axis and Y-axis parameters. Based on these maximum parameters, therapeutic exercises are rendered within so that user will be able to perform the exercise conveniently. However, in the case of severe impairment, default exercise area will be displayed to the user. By integrating the AR based therapeutic exercises in ARIS the aim is to motivate the long term engagement of the training exercise in a safe environment while different control modes of VHA model by means of biosignal and whole arm illusion concept stimulate neural plasticity to enhance fast recovery from impairments. In addition to that, ARIS surpasses the existing

MT systems which are only available for the wrist and hand movements with extra hardware apparatus in fully immersed virtual world.

5.3.6. Experiment and Results

In this section, the above developed system is tested in order to show its efficiency and the results from the experiments had been published in [218, 268]. In the test, two phases were carried out: training phase and testing phase. In training phase, all the participants received several training sessions on how to manipulate the AIRS followed by the testing phase where participants were required to perform ARIS independently. The results from both training and testing phase are also analyzed and discussed in this section.

5.3.6.1. Participants

Fifteen participants with normal eyesight and sense of touch participated in the experiment. Among them, 14 participants are right handed and one is left handed. All the participants signed an informed consent document before the experiment has conducted. Seven participants were requested to perform "Left Arm Training" while the rest performed "Right Arm Training" of ARIS.

5.3.6.2. Setting and Apparatus

The experiments were conducted in a quiet environment as the concentration of the participant is important in the ARIS experiment. To perform the experiment, each

Figure 5-8: Locations of Four Colour Markers

participant was asked to sit in front of the desk where the personal computer with webcam and FlexComp sEMG acquisition device were placed. After that, four colour markers were attached to the participant's arm as illustrated in Figure 5.8. The four sEMG electrodes were also attached to the respective positions which were indicated with four green dots as shown in Figure 5.2. Subsequently, the participant was requested to move his/her arm in circular shape freely to detect the maximum range of motion of the training arm while collecting the EMG data before the experiments. The data collected from circular motion defined the exercise area on the display screen and from EMG data, muscle activation values of all muscles were defined for *Threshold Mode*. After all the settings had been completed, participants were informed of the ARIS procedures and then were ready to receive the training sessions for the training phase.

5.3.6.3. ARIS Procedures

This section describes the procedures during manipulating of the ARIS. Before starting the exercise, user requires to choose either left or right arm training depending on which side of the arm is paralysed (in this case is requested). In addition to that, three different levels of rehabilitation therapy: initial level (*Threshold Mode*), intermediate level (*Prediction Mode*) and advanced level (*Prediction Mode*) are available in the system and user needs to choose one of the levels based on his/her arm degree of impairment. Then, the appropriate level will be displayed to the user. Step by step information is provided to the user for ease of understanding on how to manipulate the system and exercise. Before starting the exercise, the system will ask user to capture the current background so that in the later stage, this background image will integrate in the coverage object to create the illusion scene. After that, user skin colour is requested to be chosen by just clicking on the user's own skin colour which is seen on the display screen. At the same time, the VHA model which is coated with selected skin colour will be loaded in the system and be ready to be displayed to the user. Once the skin colour has been chosen and the colour markers have been attached to the shoulder, elbow and wrist joints and the finger tip, the participants will be asked to select the colour marker one by one to track the joint positions in real time and overlay the coverage object to remove the real arm on the display screen. After the real arm has been removed, VHA model will be displayed to the user by overlapping on top of coverage object. In simpler words, real arm is removed virtually and VHA is replaced to replicate the concept of mirror appearance in traditional MVF. The idea is to create the visual illusion scene to the user and "Fool-the-Brain" to stimulate neural plasticity while performing the therapeutic exercise. The attachment of the VHA model depends on the choice of level by the user. In the case of initial level, the model attaches to the rectangular box which locates at the centre of the training trajectory and *Threshold Mode* will be activated. In the case of intermediate and advanced level, VHA model attached to the user's shoulder colour marker and *Prediction Mode* will be activated. In both cases, user is required to adjust the real shoulder joint at the rectangular box in order to achieve the synchronicity between real and virtual arm. When user starts the exercise by pressing the start button, appropriate mode will be activated. In the case of *Threshold Mode*, the real-time threshold value will be checked against user predefined value and if it is above user defined level, VHA model will continue simulating along the predefined trajectory automatically. In the case of *Prediction Mode*, the continuous prediction of joint angle will be calculated and the new pose of VHA in real-time will be updated. In all levels, the performance of the real arm can be observed in real-time under real-time trajectory graph as well as in X, Y and Z positions under real hand position.

5.3.6.4. Training Phase

During traditional mirror therapy, it is important to introduce mirror visual feedback (MVF) by first demonstrating how to perceive the limb differently via MVF [269] or to perceive the virtual arm as part of own body. After that, the mirror can be introduced as a device to "Fool-the-Brain" by providing the illusion of the normal limb. This may give insight into the function of motor planning pathways. After that the patient is requested to look at the mirrored limb, without movement, and try to believe that it is his/her limb. Once the patient feels engaged with the mirrored limb, invite him/her to perform slow and easy to achieve bilateral and synchronized movements by continuing to look at the reflected image and without stopping the movements. At the same time, the therapist will check the arm behind the mirror for any signs of motor extinction. Moreover, it is necessary to conduct several trials before the patient become used to it.

In accordance with the guideline of MVF in a clinical setting as described above, during training phase of ARIS, every participant was introduced to the concept behind the ARIS, its procedures and how to perceive the VHA as his/her own real arm; these were explained so that the participant was familiar with the system. Figure 5.9 portrays the ownership illusion in ARIS. Afterwards, every participant was trained for several trials on how to manipulate the ARIS such as how to perform the therapeutic exercise, what would be the measurements and what types of measurements should be noted during the therapy session.

Figure 5-9: Ownership Illusion in ARIS System

For those participants who were novice in the AR environment and illusion concept were provided more training sessions according to user self-confidence level. There was resting time between every training session to prevent muscle fatigue. Only when the participant felt confident to perform independently, testing phase was conducted. These confidence levels of participants were evaluated by comparing the positions of real arm and virtual arm between training sessions and results are explained in section 5.3.6.6.

5.3.6.5. Testing Phase

During testing phase, every participant was expected to perform the exercise independently which is exactly the same as in the training sessions. As advised in [269], this kind of illusion therapy should be conducted little and often to fully believe in the imaginary movements which requires concentration and it seems sensible. Hence, both training and testing were conducted in a quiet environment to enhance the user concentration. As a first step of the testing phase, the evaluation of the strength of ownership perception of VHA in ARIS was conducted. Hence, participants in ARIS experiment were instructed to align real arm and virtual arm as close as possible by making use of colour markers as a baseline judgment before each trial. After that, real arm was covered by vision technology leaving the marker location with colour dot on the screen at shoulder joint and wrist joint. Then, user was requested to perform trajectory of given therapeutic exercise as if real arm is picking and placing the virtual objects while the actual pick and place was performed by overlapped VHA model without any biofeedback. The picking and placing of the virtual object was carried out by the detection of collision between virtual hand and virtual object. User was expected to move with the same speed as virtual arm's speed that was defined in the system. This is to induce the synchronous motion between real and virtual arm for high ownership perception. During the experiments, virtual arm wrist coordinates and real arm wrist marker coordinates were recorded to analyze the significant effect on ownership perception and synchronized movements via statistical analysis. In order to verify these results, statistical results were again compared with questionnaire results that were taken at the end of the testing phase.

After the evaluation of ownership illusion had been conducted, the complete ARIS system was tested. In this test, both *Threshold Mode* and *Prediction Mode* were tested. As for *Threshold Mode*, participants were asked to pretend that one of the arms was unable to move, let's say, beyond 90° in shoulder flexion and abduction. This is to mimic the condition of a patient with limited motion in shoulder ROM. After that, the maximum EMG threshold level of the participants' arm muscle which is at 90° was recorded and the recorded value was assigned to the ARIS. When the therapy was started, the initial pick and place actions were done by real arm up to maximum threshold level and beyond this, VHA model took over the job of the real arm. In this mode, VHA was automatically simulated based on predefined trajectory. As for the *Prediction Mode*, the patients were

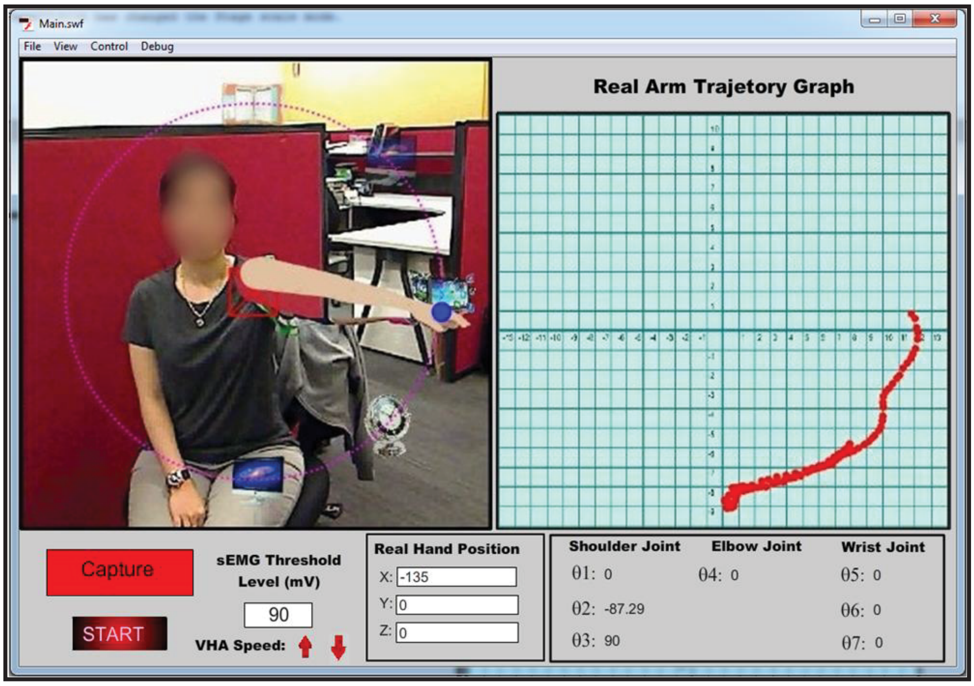


Figure 5-10: The screen shot of one participant in "Right Arm Training" with *Threshold Mode*

instructed to perform pick and place actions by real arm and the simulation of the VHA model was driven by predicted joint angles. The simulation speed of VHA model in ARIS was manually defined to maximize the synchronicity between real and virtual arm. The screen shot of Testing Phase in ARIS is presented in Figure 5.10.

5.3.6.6. Result Discussion

In this section, there are four types of evaluation results which are discussed from both training and testing phase. From training phase, the confidence levels of participants were studied to make sure that the participants had received enough training sessions in order to move on to testing phase where they performed the ARIS independently. After that, the ownership effects in ARIS were evaluated which is one of the most important contributions in ARIS. After the ownership illusion effect has been discussed, the results from the testing phase which includes the results of *Threshold* and *Prediction Mode* were discussed. Finally, the overall effectiveness of the ARIS system was discussed via evaluating the Questionnaires results which were conducted at the end of the experiment.

Initially, from the training phase, the participants' level of confidence was evaluated by one-way repeated measures analysis of variance (ANOVA). This tool can help us to evaluate the performance of repetitive training over time. The significance level was set to $\alpha = 0.05$, and the corresponding results of this test are shown in Table 5.1. The ANOVA results clearly indicate that the repetitive training sessions enhanced the accuracy of the trajectory performance over time with PPR ($\boldsymbol{F}(1,15) = 10.627$, $\boldsymbol{p} = 0.207 \times 10^{-3}$) and CMR ($\boldsymbol{F}(1,15) = 10.143$, $\boldsymbol{p} = 0.22 \times 10^{-3}$). Therefore, the more training was provided, the better the accuracy of the results achieved as participants learnt from the experience. The corresponding error rates resulting from training sessions are shown in Figure 5.11.

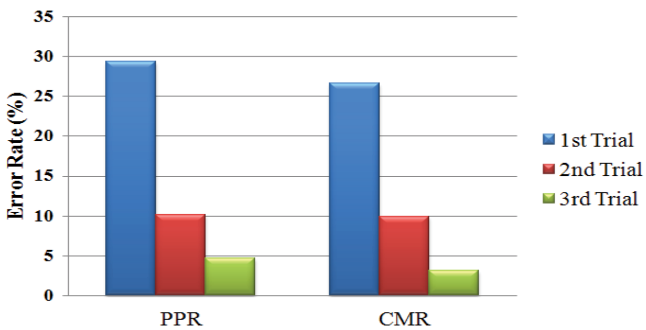


Figure 5-11: Error rates achieved via different training sessions in PPR and CMR

Table 5.1: Results of one-way repeated measures ANOVA on trajectory

Method	***P-value***
PPR (across Trial 1, Trial 2, Trial 3)	0.207×10^{-3}
CMR (across Trial 1, Trial 2, Trial 3)	0.284×10^{-3}

In addition to that, trajectory performance of graphical representations was displayed on the monitor as an immediate feedback to the users and therapists as a part of motivation and immediate performance evaluations. The example of graphical representation in CMR is portrayed in Figure 5.12. From this visual feedback, it was clearly seen that after the third training session had been conducted, the trajectory became very smooth compared to the first one. During the first training session, the movement trajectory that was performed by subject 10 was scattered a lot as shown in Figure 5.12(a). However, the scatter range was improved during the second training and third training as the subject learned how to perform the exercise and able to control his own movement. This result shows that subject 10 had achieved self-confidence after the third session of CMR exercise to proceed to the next phase; the testing phase. It also shows that the therapeutic exercise in ARIS is easy to understand and able to be adapted to quickly which will offer great benefit to the paralyzed patients. In additional to that, these visual feedback results agreed with the results from the ANOVA test and hence it can be concluded that the graphical presentation is a quick and reliable tool to evaluate patient performance immediately in the ARIS system by therapists.

Secondly, the ownership perception and synchronicity in ARIS was evaluated by 2x2 repeated measures using ANOVA. The significance level was set to $\alpha = 0.05$ with the

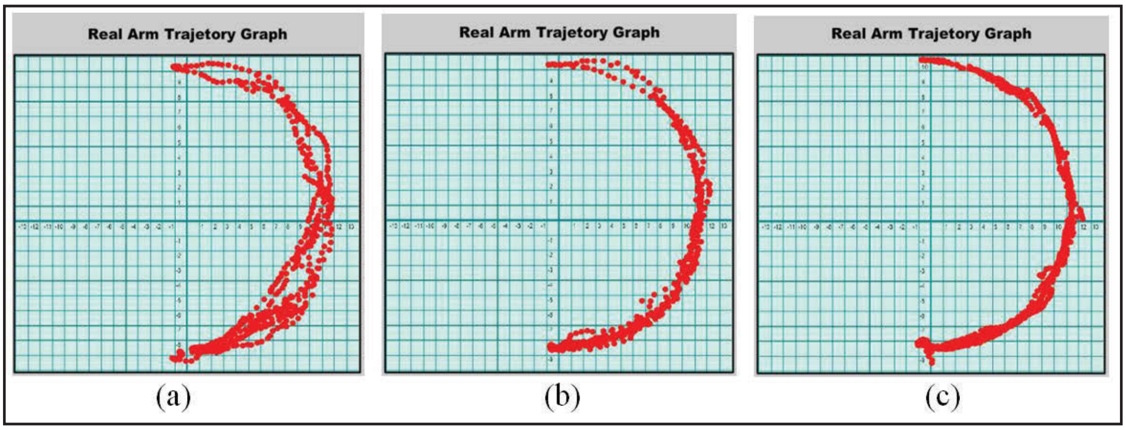
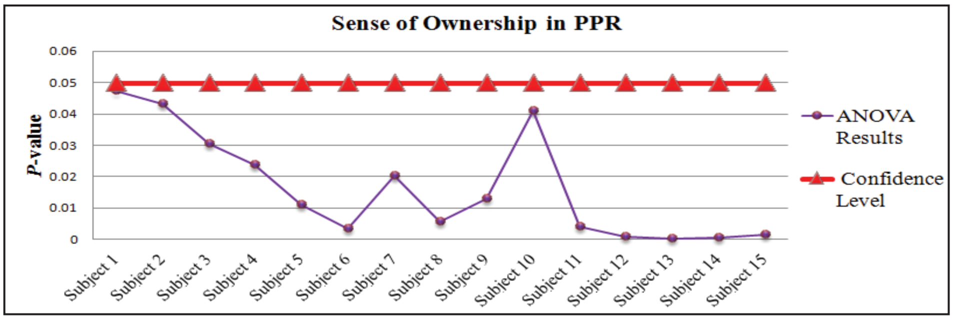


Figure 5-12: Screen shots of right arm performance of subject 10 in CMR exercise during training phase (a) after 1st trial (b) after 2nd trial and (c) after 3rd trial

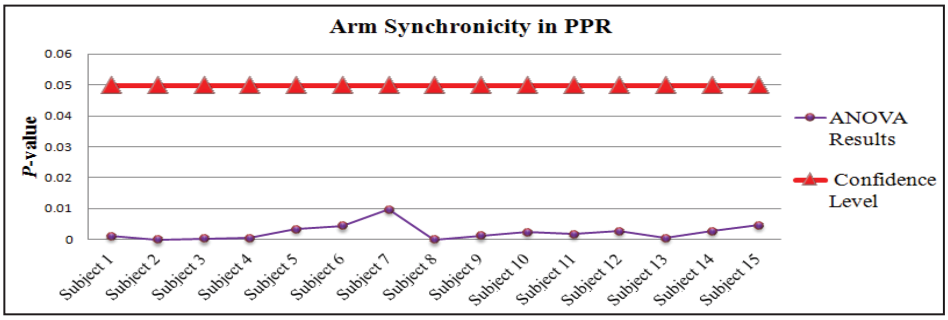
factors of ownership (real arm and virtual arm) and arm synchronicity (real arm and virtual arm). The results showed that significant main effect of ownership was found ($\boldsymbol{p} < 0.05$) on most of the test results as well as significant main effect of arm synchronicity ($\boldsymbol{p} < 0.05$) was found. It was also revealed that the interaction between the two factors was highly significant ($\boldsymbol{p} < 0.01$) from the test. The overall test results across fifteen subjects for PPR and CMR exercises are plotted in Figure 5.13. From the figure, there were some participants that did not perceive the illusion as an own arm due to failing to track the marker or did not synchronize the movement between virtual and real arm. Due to the tracking error, the coverage of the real arm was lost and it was seen by the participant and this led to a disturbance of the concentration of imagination during the experiment. As a result, the synchronized movements between real and virtual arm was disturbed and the ownership feeling of the participant was lost. Overall, from the test results, it can be concluded that the illusion perception was induced when the synchronized movements were provoked and such illusion was able to be stimulated in the ARIS system.

After ownership illusion had been tested, the effectiveness of *Threshold Mode* and *Prediction Mode* were evaluated. In the case of *Threshold Mode*, it was found that simulation of VHA model was successfully performed in every exercise by comparing the predefined threshold value with real-time recorded threshold value from user's muscles. It was also found that to be able to perform successful takeover job by VHA, synchronicity is important because if there is an error between real hand location and virtual hand location, the collision cannot be detected and therefore, the virtual object could not be transferred from real hand to virtual hand. This conclusion was affirmed by one-way ANOVA results, ($\boldsymbol{F}(1,15) = 16.389$, $\boldsymbol{p} = 0.000412$) where the synchronicity in both hands has significant effects on the takeover action.

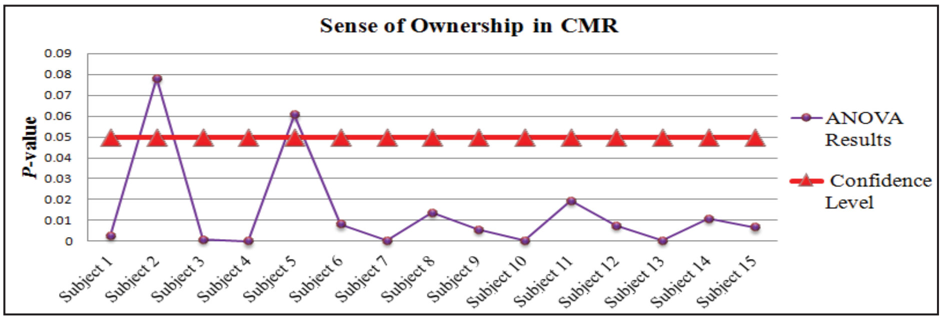
During *Prediction Mode*, the continuous prediction of joint angles from user's EMG were sent to the VHA model and with these predicted angles, the model is driven synchronously with real arm. The data for both real and predicted angles were taken at every 5° apart for evaluation. The real arm joint angle was calculated via webcam captured marker locations: shoulder, elbow and wrist joint. The average error between real and predicted angle for PPR and CMR is represented in Figure 5.14. The result shows that the angles were able to be predicted with a very high level of agreement and the average time taken for updating the new pose of VHA model was 38 ms which is considered as a real-time simulation. However, too much angle deviation may have an effect on the user's



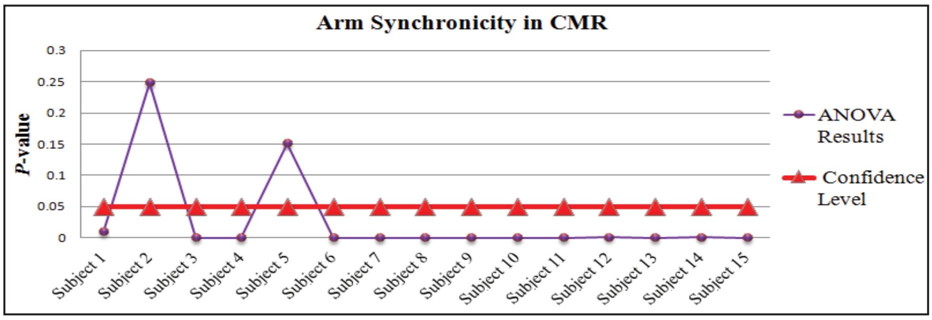
(a) Result of two-way repeated ANOVA on sense of ownership in PPR



(b) Result of two-way repeated ANOVA on arm synchornicity in PPR



(c) Result of two-way repeated ANOVA on sense of ownership in CMR



(d) Result of two-way repeated ANOVA on arm synchornicity in CMR

Figure 5-13: Results of two-way repeated ANOVA on sense of ownership and arm synchronicity in PPR and CMR exercises

illusion perception and hence, the one-way ANOVA with $\alpha = 0.05$ was carried out in all conditions to find out whether the angle deviations in ARIS were affected by the ownership illusion or not. It was found that there was no significant effect in all conditions:

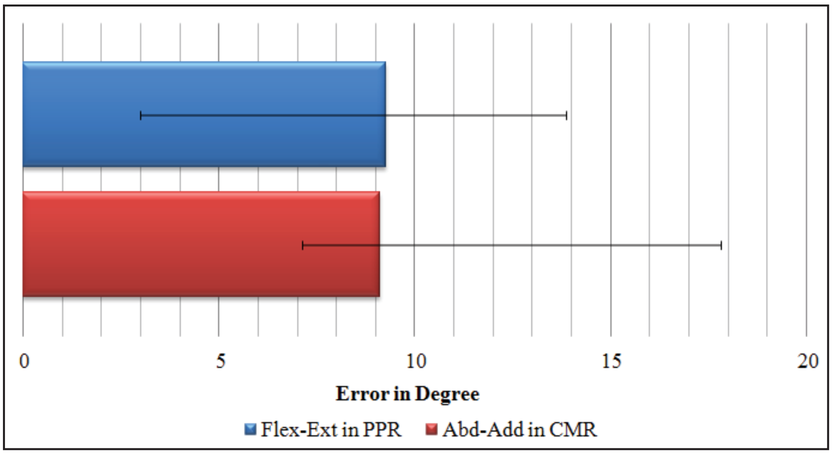


Figure 5-14: Average error graph between real and virtual joint angle

flexion-extension in PPR ($\boldsymbol{p}$ = 0.3978) and abduction-adduction in CMR ($\boldsymbol{p}$ = 0.662). In other words, although some deviation of angles was found in *Prediction Mode*, the ownership perception was not affected and ARIS was able to perform as intended.

After the *Testing Phase* has completed, two sets of questionnaires were conducted. Questionnaire A was conducted for participants' experience of their arm through the display screen [259]. Questionnaire B was conducted for overall ARIS experience. The answers for the questionnaires are in accordance with the visual-analogue likert scale where "5" refers to strongly agree and "1" refers to strongly disagree. The set of questions that were asked in the Questionnaires A and B are described in the Appendix A3.

The first part of the questionnaire, Questionnaire A, which accessed the feeling of ownership illusion result is depicted in Figure 5.15. From the results, as predicted, the responses are very much encouraging and these aligned with the evaluated results from ANOVA test on sense of ownership and synchronicity. During the exercise, most of the participants felt as if real arm was moving together with virtual arm. They also felt that when they had the intention to move their real arm, the virtual arm was moved at the same time. As a result, VHA movement encouraged the real arm to move again. In simpler words, synchronized motion was felt. Although the pick and place was done by VHA, participants felt as if the real arm was performing the exercise. Most of the participants felt VHA was part of their own body within a good illusion environment.

The second part of the questionnaire, Questionnaire B results are portrayed in Figure 5.16. It can be clearly seen that all the participants found the experience interesting and enjoyable during the experiment. All the participants received adequate training sessions as

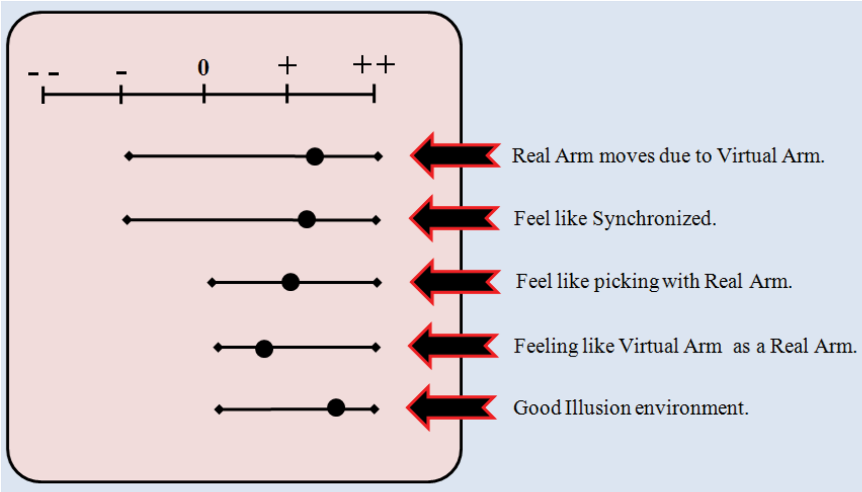


Figure 5-15: Results of “Questionnaire A” on feeling of ownership perception in ARIS

well as information and procedure on how to perform and manipulate the ARIS. Most of the participants also found that the multiple colours tracking technique that developed in ARIS was good. Most of the time, all the colour markers were able to be tracked except sometimes in training phase, some colour markers were out of the webcam picture as some of the participants were not familiar with webcam applications and AR technology. They also felt that collision detection was good because it was very stable in picking and placing the virtual object. The exercise that was integrated in ARIS was also reported to be very easy to understand and manipulate and also participants felt a good sense of immersion in AR environment. The threshold level of anterior deltoid that was defined before training and testing phase was good and VHA model was receiving real-time activation commands to simulate the model. As far as muscle fatigue was concerned, none of the participants felt any muscle fatigue during training and testing phase as they were given enough rest between each session. Based on the different forms of analysis and evaluations in ARIS, the experience with ARIS was positive. These findings confirmed that the use of the ARIS system in clinical settings is feasible for upper limb rehabilitation therapy.

5.4. Demonstration in Port Kembla Hospital

One of the goals of our developed rehabilitation systems are intended to reduce physiotherapists’ work load by replacing with minimum supervised augmented reality based games. Therefore, several discussions and consultations with physiotherapists from Port Kembla Hospital were carried out for the best rehabilitative game design and their requirements. Our developed exercises give simple yet motivating feedback for the

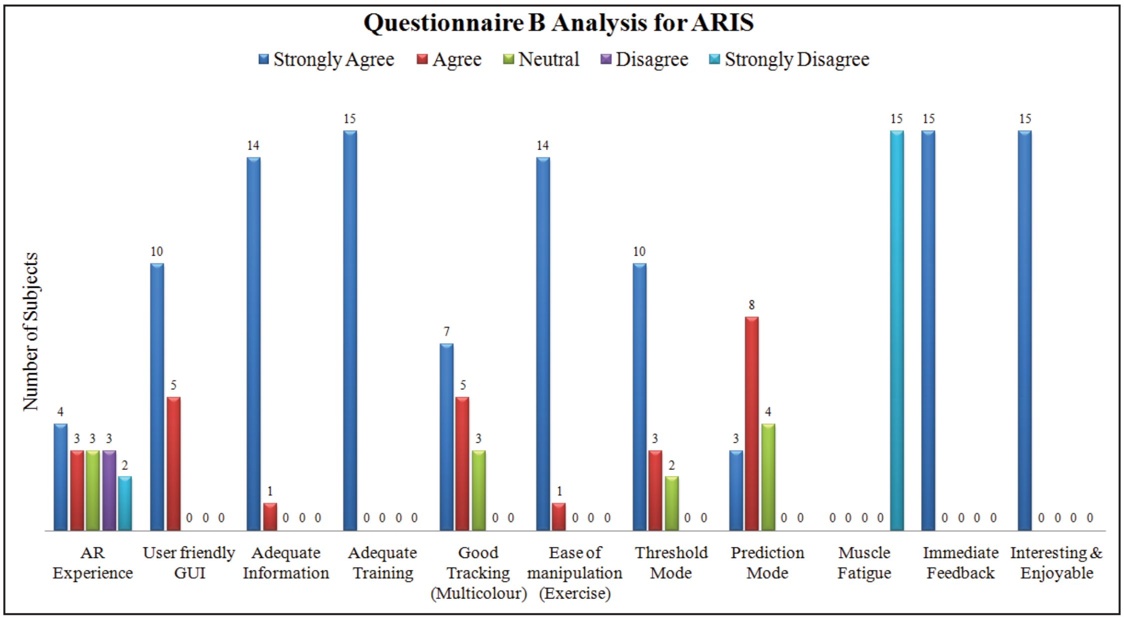


Figure 5-16: Results of “Questionnaire B” for ARIS

players’ performances, are difficult enough to induce personal effort during the movement for fast recovery without losing the engagement, and facilitate data collection during the game play for post processing. We have demonstrated our system to clinical professionals (Dr. Namuk Al-Khateeb, Senior Staff Specialist in Rehabilitation and pain Medicine, and his team, Dr. Geoffrey Murray, Divisional Director of Rehabilitation Medicine, and his team) at Port Kembla Hospital which specialises in rehabilitation, aged care and palliative care services located at Warrawong, New South Wales. Firstly, we presented our aims, comparison between traditional rehabilitation exercises and our exercises, the value-added services that are integrated in our system and benefits from our developed system. After the demonstration, clinical professionals responded with very positive feedback as follows:

- The exercises are very motivating and would be very useful for paralysed patients due to any neurological deficits.
- TOR exercise would be very suitable for SCI patients.
- All of the exercises are well developed for eye-hand coordination that will provide great benefits for the patients.
- Developments of different exercises with different level of motions and cognitions for different recovery stage of patient are appropriate.
- Biofeedback simulation is very motivating for both patients and therapists.
- Ability to track the EMG threshold level is a great advantage for therapists to evaluate the patients’ performance along the therapy sessions.

- The developments seem likely to help in fast recovery for any level of paralysed patients but “how fast” is can be answered by the conduct of clinical trials.

Due to the above positive feedback from clinical experts, our developments have been considered as a recognized system that is suitable for all level of paralysed patients. In addition to that, clinical experts are happy to conduct the clinical trials with their patients and necessary administration requests are underway.

5.5. Summary

In this chapter, the development of ARIS was discussed as a fourth contribution of this thesis. In ARIS, all the factors that are defined as an effective rehabilitation system were integrated to serve as a complete novel system. These factors include decoupling, beliefs and interaction. The decoupling of physical from mediated domain is the main defining feature for the effectiveness of ARIS system. The user’s real arm was virtually disconnected by introducing a barrier (the coverage) and reconnected on the screen by overlaying the VHA to substitute for the real arm to perform the developed therapeutic exercises in AR environment. The user has to believe that the mediated experience is real, for instance, virtual arm, VHA, as part of user’s body to stimulate the user’s premotor cortex which plays a role in planning movement, spatial guidance of movement, performing specific tasks, sensory guidance of movement and understanding the actions of others. This stimulation will excite the nature of neural plasticity in the affected area. The decoupling and beliefs in ARIS was evaluated and its effectiveness proven statistically. Last, but not least, the interaction is one of the main aspects in manipulating the judgment and reality. It is determined by its ability to respond to user’s actions with immediate feedback, and in the case of ARIS, real time biofeedback, immediate visual and audio feedback and an enhancement in motivation and motor recovery. The developments were analyzed and evaluated by means of statistical methods, responses from immediate feedback and sets of Questionnaires with positive results. In addition to that, demonstrations have been conducted at Port Kembla Hospital and feedback has been very encouraging. These positive results encourage our developments to be employed in clinical settings as a novel upper limb rehabilitation system.

Chapter 6
Summary, Conclusion and Future Research

In this chapter, the summary of the thesis and the major findings of the research performed are given. After that, the future research that may be conducted in relation to this thesis area of research is also described.

6.1. Thesis Summary

In this thesis, four novel contributions in the field of upper limb rehabilitation are proposed.

In **Chapter three**, the RehaBio system was developed as a first contribution of this thesis. The developed system was made up of five cost effective therapeutic exercises and real time biofeedback simulation. All the exercises in RehaBio were developed in an AR environment to enhance the motivation with a safer training environment for upper limb impaired patients. In addition to that, all the exercises can be performed under minimum supervision of therapists. Along with the guidelines for physical rehabilitation exercises in a clinical setting, the upper limb rehabilitation exercises were imitated in an AR environment with additional immediate audio and visual feedback. In AR environment, patients are required to interact with virtual objects with their impaired arm to accomplish the task where their arm movements enhance muscle strength and range of motion in the upper limb. Additionally, integrating the custom made real-time biofeedback simulation with therapeutic exercises in the RehaBio system enhanced user engagement to perform therapeutic exercises longer. The performance of the system was evaluated by data analysis, performance analysis and questionnaire. The results and feedback from analysis and questionnaire were very encouraging. Therefore, RehaBio is able to close the major gaps such as expensive health care cost, requirement of one-to-one attention between patient and therapist and also boring traditional rehabilitation exercise in the rehabilitation field.

In **Chapter four**, the real time control algorithm based on biosignal was proposed along with the description of the development of the VHA model as a second and third contribution of this thesis. The controller is designed to predict the joint angle in real time which is based on the user's sEMG signal to drive the VHA model. Two muscle activation methods namely NMA and TDF are considered and evaluated their accuracies in proposed prediction models; ELM based regression model and BPNN based prediction model. Subsequently, the outcomes from the proposed joint angle prediction models are evaluated in offline mode. The result showed that ELM based regression model with NMA activation method provided the best accuracy with better computational cost. Therefore, this model was chosen as an optimal controller for the VHA model in real time. The development of the VHA model along with its mathematical model is also described in this chapter. Forward and inverse kinematics was defined properly to perform the simulation according to the user's biological signals. The simulation of real time biosignal driven model with VHA model is performed to evaluate the effectiveness. It was found that the accuracy of the joint angle prediction was higher with less computational cost than with the compared model. In addition, the predicted angles were able to be sent to simulate the VHA model in less than 40 ms which is required for real time applications.

In **Chapter five**, illusion or "Fool-the-Brain" concept was introduced to stimulate the neural plasticity which enhances in motor recovery as a fourth contribution in this thesis. Illusion concept was induced by accessing the ownership perception of the virtual model as part of the body. The idea is removing the impaired real arm virtually and attaching with the virtual arm on computer display screen which mimics the job of real arm. By introducing the VHA model virtually and simulation via technology, the job that cannot be performed by the impaired arm will appear as if the real arm is able to perform it and this perception will reorganize the neural circuitry to encode new experiences and enable behavioral changes. With this concept, the complete upper limb rehabilitation system, ARIS, was developed as a novel rehabilitation system. ARIS is made up of motivated AR based exercises as rehabilitation training, enriched with immediate audio and visual feedback, stimulating the brain plasticity via the illusion concept by means of VHA model and integrate this with biofeedback to provide stimulus driven by unconscious body functions to make users aware of them and learn how to control them. Since the whole system was developed via computer vision technology, there is no additional hardware such as mirror box or head mounted display are needed and therefore the developed system is very low cost which can afford by every patient. The evaluation of the ARIS was conducted via statistical method, visual method and questionnaires method. In addition, all the developments have been demonstrated in Port Kembla Hospital and valuable feedback with very encouraging responses were received. From the analysis results, it was also found that very encouraging responses were received and therefore, ARIS is possible to be employ in clinical settings as a novel upper limb rehabilitation system.

6.2. Recommendation for Future Research

From this research, a number of research tracks have been uncovered that may improve further in rehabilitation. The following issues are recommended for future research in the field of this thesis.

- In the context of therapeutic exercise, it is necessary to develop more upper limb exercises that will be engaging in the long term via a motivational approach. This can be done via introducing the multiplayer games in which patients play together with friends and family members, creating the online communities that enable the patients to meet and interact with people in similar conditions, and enable them to play online games together. These approaches can help games be part of a social activity shared with family members and friends, and help patients to create social habits around them.
- In the context of ownership illusion, although VHA model in this thesis is proven to induce the illusion perception, further improvement on the model is required for realistic appearance. This should be inexpensive and be reliable for large variations in shape, size and clothing worn by patients. This can be completed by developing the model based reconstruction of shape from silhouettes and creating the multiple views of real arm colour images. From reconstruction, a 3D generic humanoid model will be transformed to approximate to a person's arm shape and anatomical structure. Also the realistic appearance will be achieved by color texture mapping from the captured images from multiple views of the real arm.

- To make a system more interactive with the patients, the interactive virtual therapist that will guide the rehabilitation therapist throughout the therapy can be added. This can serve as a personal professional trainer and greatly benefit the patients who are not comfortable to interact closely with strangers. The role of the virtual therapist is to explain the whole process of the particular training verbally. In addition, the virtual therapist will demonstrate how to perform the therapeutic exercises before the training as well as if the patients do not perform the exercise correctly during the training. However, monitoring of the individual performance and evaluation of the outcome will be still analyzed by professionals, therapists.
- The developed home based system can be improved to operate in a tele-rehabilitation setting. In order to create this setting, a web based library of status tests and performance results from rehabilitation exercises is required to be developed. In addition, low cost webcam can be incorporated to observe the user's activities during the system use in real time via tele-conferencing software or post evaluation via recording and storing in the web based library. With this setting, clinical professionals can monitor the progress of the patients and manipulate the exercises as required and provide instructions remotely. This will provide several benefits to the paralysed patients by saving money and travel time to rehabilitation centers reducing the tiredness from travelling and the patient can perform the rehabilitation conveniently at home.

6.3. Conclusion

In this thesis, novel upper limb rehabilitation systems were developed and proven to enhance the recovery from limited motions in an upper limb. In contrast to other therapeutic exercises, effective and motivated AR based upper limb rehabilitation exercises were developed by integrating with real time biofeedback simulation. In addition to that, illusion concept was employed to stimulate the brain plasticity to enhance the motor recovery in a faster approach. The control method of the VHA model which creates the illusion concept, additionally enhanced the excitation of the brain plasticity nature by means of own biosignal, sEMG. The evaluation results, from statistical analysis, usability tests and feedback from clinical professionals were very encouraging to serve as a novel upper limb rehabilitation system in a clinical setting. The future research directions discussed above are surely going to lead to improvements based on current contributions as a complete effective tele-rehabilitation system for upper limb rehabilitation.

Appendix A

A.1 Comparison Table from Literature

End-Effector based Rehabilitation System								
Author	**D.O.F**	**Name**	**Supported Movement**	**Main Input**	**Market Availability**	**Motivation and Neural Plasticity Aspect**	**One-to-One Attention**	**Costing Aspect**
M. P. Dijkers, et al. [68]	6	N.A	Shoulder, Elbow	Predefined positions	No	None	High	High
R. Rao, et al. [270]	6	Puma-260	Shoulder, Elbow	Force, End point position	Yes	Medium	High	High
A. Toth, et al. [74]	12	REHAROB	Shoulder, Elbow	Predefined positions	Yes	None	High	High
H. I. Krebs, et al. [76, 77]	4	MIT-Manus	Shoulder, Elbow, Wrist, Hand	Joint positions, Angular Velocity, Torque	Yes	Medium	Medium	High
D. J. Reinkensmeyer, et al. [78]	3	ARM Guide	Shoulder, Elbow	Forearm position and torque	No	None	Medium	Medium
S. Micera, et al. [271]	2	MEMOS	Shoulder, Elbow	Torque, Handle position	No	Low	Medium	Medium
G. Rosati, et al. [272]	5	MariBot	Shoulder, Elbow	Motor positions	No	Low	High	High
F. Brooks, et al. [80]	3	GEOPE	Shoulder	Force, Torque	No	High	High	High

Author	D.O.F	Name	Supported Movement	Main Input	Market Availability	Motivation and Neural Plasticity Aspect	One-to-One Attention	Costing Aspect
J. T. Dennerlein, et al. [81]	2	N.A	Shoulder	Force, End point position	No	High	Medium	Medium
P. Gallina, et al. [83]	3	Feriba-3	Shoulder, Elbow	Force	No	None	High	Medium
J. Broeren, et al. [85]	6	N.A	Shoulder, Elbow, Hand	Force	Yes	Medium	Medium	High
G. Shuxiang, et al. [86]	6	PHANTOM Omni	Shoulder, Elbow, Hand	Force	Yes	Medium	Medium	High
T. H. Massie, et al. [273]	6	N.A	Hand	Torque	No	Medium	Medium	High
W. Harwin, et al. [89]	6	Gentle/S	Shoulder, Elbow, Forearm	End point torque, position, velocity	Yes	Medium	High	High
M. J. Johnson, et al. [94]	1	SEAT	Shoulder	Force	No	Medium	Medium	High
C. G. Burgar, et al. [274]	6	MIME	Shoulder, Elbow	Forearm position, orientation, torque	No	Medium	High	High
P. S. Lum, et al. [98]	1	N.A	Wrist	Force	No	None	High	Medium
S. Hesse, et al. [99]	2	N.A	Elbow, Wrist	Force	No	None	High	Medium
E. Rashedi, et al. [100]	2	N.A	Elbow, Wrist	Force	No	Low	High	Medium
J.-J. Chang, et al. [101]	2	BFIAMT	Shoulder, Elbow	End point position, torque	No	None	High	High
L. Chunguang, et al. [102]	1	N.A	Forearm	Torque	No	None	High	Medium
External Force Exoskeletons								
T. Rahman, et al. [275]	4	N.A	Shoulder, Elbow	Force	No	None	High	Medium
M. J. Johnson, et al. [94]	1	SEAT	Shoulder	Force	No	Medium	Medium	High

Author	D.O.F	Name	Supported Movement	Main Input	Market Availability	Motivation and Neural Plasticity Aspect	One-to-One Attention	Costing Aspect
T. Nef, et al. [11, 276]	7	ARMin III	Shoulder, Elbow, Forearm, Wrist	Joint angles, grasp force	Yes	Low	High	High
S. J. Ball, et al.[107]	3	MEDARM	Shoulder, Elbow	Force	No	None	High	Medium
R.A.R.C.. Gopura, et al. [277]	7	SUEFUL-7	Shoulder, Elbow, Forearm, Wrist	sEMG, Joint force, torque	No	None	High	High
R. Yupeng, et al.[110]	10	IntelliArm	Shoulder, Elbow, Forarm, Wrist, Fingers	Joint angles, torques	No	None	High	High
B. C. Tsai, et al. [111]	9	N.A	Shoulder, Elbow, Forearm, Wrist,	EMG, Force	No	None	High	High
D. Koo, et al. [278]	6	RPRPRR	Shoulder	Force	No	None	High	High
A. H. A. Stienen, et al. [113]	4	Limpact	Shoulder, Elbow	Joint angles, torques	No	None	High	High
S. Kousidou, et al. [279]	7	SRE	Shoulder, Elbow, Forearm, Wrist	Position, torque, Actuators pressure	No	None	High	Medium
Internal Force Exoskeletons								
S. Balasubramanian, et al. [280, 281]	5	RUPERT	Shoulder, Elbow, Forearm, Wrist	Joint torques, Actuators pressure	No	High	Medium	Medium
C. Carignan, et al. [117]	5	MGA	Shoulder, Elbow, Forearm	Joint torques	No	None	High	High
T. Lenzi, et al. [118, 282]	4	NEUROExos	Elbow	Joint torque	No	None	High	High
P. Garrec, et al. [283]	7	ABLE	Shoulder, Elbow, Forearm, Wrist	Force, positions	No	High	High	High
P. S. Lum, et al. [98]	1	N.A	Wrist	Force	No	None	High	Medium

Author	D.O.F	Name	Supported Movement	Main Input	Market Availability	Motivation and Neural Plasticity Aspect	One-to-One Attention	Costing Aspect
Y. Hasegawa, et al. [69]	3	N.A	Elbow, Wrist, Fingers	Head Motion	No	None	High	Medium
M. C. Carrozza, et al. [120]	2	N.A	Wrist	Positions	No	None	High	Medium
Alignment-Free Exoskeletons								
T. Lenzi, et al. [118, 282]	4	NEUROExos	Elbow	Joint torque	No	None	High	High
J.C. Perry, et al. [284]	2x7	CADEN-7	Shoudler, Elbow, Forearm, Wrist	sEMG, Joint angles, Angular velocities, Force/ Torques	No	None	High	High
B. Dehez, et al. [285]	2	ShouldeRO	Shoulder	Force	No	None	High	N.A
S. Zhibin, et al. [123]	1	N.A	Elbow	Force	No	None	High	N.A
L. E. Amigo, et al. [125]	3	N.A	Elbow	Force	No	None	High	N.A
A. Gupta, et al. [286]	5	MAHI	Elbow, Forearm, Wrist	Joint angles	No	None	High	High
Virtual Reality based Rehabilitation Systems								
L. Yingzhu, et al. [287]	7	N.A	Shoulder, Elbow, Forearm, Wrist	Head Tracker, Hand Tracker	No	Medium	Medium	Low
J. Jacobson, et al. [132]	Not stated	BNAVE	Whole Body	Sensors, trackers	No	Medium	Medium	Low
S. Adamovich, et al. [133]	27	N.A	Fingers	CyberGlove,CyberGrasp	Yes	Medium	High	Medium
P. Chan-young, et al. [134]	27	N.A	Fingers	Sensors, Joint angles	No	Medium	Medium	Medium
G. Shuxian, et al. [86]	6	PHANTOM Omni	Shoulder, Elbow, Hand	Force	Yes	Medium	Medium	High
M. Sha., et al. [288]	2	N.A	Wrist, Hand	sEMG	No	Medium	Medium	Low

Author	D.O.F	Name	Supported Movement	Main Input	Market Availab ility	Motivation and Neural Plasticity Aspect	One-to-One Attention	Costing Aspect
B. M. Odle, et al.[136]	2	Hands-Up	Shoulder, Elbow	Marker	No	Medium	Low	Low
J. E. Cifuentes-Zapien, et al. [137]	1	N.A	Forearm	Rotation angles	No	Medium	High	High
Augmented Reality based Rehabilitation Systems								
J.W.Burke, et al. [141, 289]	4	N.A	Shoulder, Elbow	Colour Marker	No	High	Medium	Low
A. Alamri, et al. [143]	7	AR-Rehab	Shoulder, Elbow, Hand	Tracking devices, Pattern marker	No	High	Medium	Medium
A. Toh, et al. [290]	7	Rehab@Ho me	Shoulder, Elbow, Hand	Pattern marker	No	High	Medium	Low
Dunne et al. [145]	2	N.A	Hand	Multitouch display, tangible object, accelerom eter	No	High	Medium	High
E. Richard, et al.[146]	3	ARVe	Shoulder	Pattern marker	No	High	Medium	Low
T. Chau, et al.[291]	6	N.A	Shoulder, Elbow, Hand	Motion detection sensors	No	High	Medium	Medium
A. G. D. Correa, et al.[292]	2	N.A	Shoulder, Elbow	Color pattern marker	No	High	Medium	Medium

A.2 Algorithms

In this Appendix some fragments of code from proposed systems are presented and detailed about these algorithms are explained in respective chapters.

Algorithm 3.1 AABB Vs. AABB

Given four bodies with AABBs in BCR exercise are shown in Figure 3.24.

Step 1: Define all the bodies' coordinate system in the world space.

Step 2: Transform world space to local space coordinate system to optimize the accuracy and computational load.

Step 3: Define the centres (C_x) and their half-extents (HE_x) of all the bodies.

Step 4: Calculate the difference between centres ($|C_2-C_1|$) of interest bodies for all bodies:

Case1: *Body A vs. Body B;*

Case2: *Body A vs. Body C;*

Case3: *Body A vs. Body D;*

Case4: *Body B vs. Body C;*

Case5: *Body B vs. Body D;*

Case6: *Body C vs. Body D;*

Step 5: Calculate the total half-extents for both bodies of interest ($HE_1 + HE_2$) for all bodies.

Case1: *Body A vs. Body B;*

Case2: *Body A vs. Body C;*

Case3: *Body A vs. Body D;*

Case4: *Body B vs. Body C;*

Case5: *Body B vs. Body D;*

Case6: *Body C vs. Body D;*

Step 6: Calculate the difference D = | C_2-C_1 | - (HE_1 + HE_2) between bodies of interest for all bodies.

Case1: *Body A vs. Body B;*

Case2: *Body A vs. Body C;*

Case3: *Body A vs. Body D;*

Case4: *Body B vs. Body C;*

Case5: *Body B vs. Body D;*

Case6: *Body C vs. Body D;*

Step 7: If Dx <= 0 && Dy <= 0, two bodies are "Collide" and do the following action!

If Dx <= 0 && Dy <= 0 *for A vs. B*

Do (nothing);

If Dx <= 0 && Dy <= 0 *for A vs. C*

Do (nothing);

If Dx <= 0 && Dy <= 0 *for A vs. D*

Do (pick up action);

If Dx <= 0 && Dy <= 0 *for B vs. C*

Do (nothing);

If Dx <= 0 && Dy <= 0 *for B vs. D*

Do (Pick-up Action);

If Dx <= 0 && Dy <= 0 *for C vs. D with A pick up action*

Do (Wrong Choice Action!);

If Dx <= 0 && Dy <= 0 *for C vs. D with B pick up action*

Do (Placement Action!);

Step 8: Loop from Step 4 to Step 7 to check all the collision in every frame captured by webcam.

Algorithm 3.2: Approximation Queries

(Fragment of code is extracted from BCR exercise)

```
…….
var rectPoint:Point = new Point((rect.x+rect.width/2), (rect.y+rect.height/2));
var pinkBall:Point = new Point (pBalls[i].x, pBalls[i].y);
var greenBall:Point = new Point (gBalls[i].x, gBalls[i].y);
var box:Point = new Point (Box.x, Box.y);

if (Point.distance(pinkball, rectPoint) < 5)
{
        Pick-up action!
}

if (Point.distance(box,rectPoint) < 5 && Point.distance(greenBall,rectPoint) > 10)
{
        Placement Action!
}       ……..
```

Algorithm 4.1: Simple learning algorithm for ELM [171]

Given a training set $\Re = \{(x_i, t_i) | \; x_i \in R^n, t_i \in R^m, i = 1, \ldots, N\}$ with activation function g(x) and hidden node number $\widetilde{N}$.

Step 1: The input weight $\boldsymbol{w_i}$ and bias $\boldsymbol{b_i}$ are assigned randomly where $i = 1, \ldots, \widetilde{N}$.
Step 2: Calculate the hidden layer output matrix $\boldsymbol{H}$.
Step 3: Calculate the output weight $\boldsymbol{\beta}$.

Algorithm 4.2: Code Fragments to load the VHA model in Flash

```
// importing of 3D graphic engine class
import org.papervision3d.*
```

```
…
//defining the related variables for VHA model, material and color
private var _obj:DAE;
private var material:GouraudMaterial;
private var materials:MaterialsList;
private var light:PointLight3D;
private var renderer :BasicRenderEngine;
private var scene:Scene3D;
private var camera:Camera3D;
private var viewport:Viewport3D;
…
// Get the user defined skin color for VHA
skinColour = bmd.getPixel(this.mouseX, this.mouseY);
….
// Apply the chosen color to the model
light = new PointLight3D(true,false);
material = new GouraudMaterial(light, skinColour, 0x666666, 150);
materials = new MaterialsList( );
…
//Load all the segments and joints of the VHA model and adjust the orientation and scale to
align with Flash orientation
_obj = new DAE(false, "LeftArm");
_obj.load("leftArm.dae",materials);
_obj.scale = 400;
_obj.rotationY = 180;
_obj.rotationX = -90;
scene.addChild(_obj);
…
renderer.renderScene(scene, camera, viewport);
…
//Assign the variables in each joint, θ for F-K & I-K calculation
// for θ1, θ2, θ3
```

```
var humerus:DisplayObject3D =
_obj.getChildByName("COLLADA_Scene").getChildByName("ShoulderJoint");
// for θ4
var ulna:DisplayObject3D =
_obj.getChildByName("COLLADA_Scene").getChildByName("ShoulderJoint").
getChildByName("ElbowJoint");
// for θ5, θ6, θ7
var hand:DisplayObject3D =
_obj.getChildByName("COLLADA_Scene").getChildByName("ShoulderJoint").
getChildByName("ElbowJoint"). getChildByName("WristJoint");
// for VHA finger tracking in real time
var finger:DisplayObject3D =
_obj.getChildByName("COLLADA_Scene").getChildByName("ShoulderJoint ").
getChildByName("ElbowJoint ").getChildByName("WristJoint ").
getChildByName("MiddleFinger1");
…
//Do this
{
        "Threshold Mode" or "Prediction Mode"
        ARIS Exercise
}
```

A.3 Questionnaires

The questionnaires utilized in this research to evaluate the effectiveness of the proposed rehabilitation systems are described in this appendix. There are two questionnaires in this thesis which are evaluated for RehaBio and ARIS system respectively. All the answers for the questionnaires are in accordance with the visual-analogue likert scale where '4' refers to strongly agree and '1' refers to strongly disagree.

Below are the details for each questionnaire.

A.3.1 RehaBio System

A physical rehabilitation questionnaire is conducted for RehabBio system to analyze the effectiveness of the developed system. The set of questions in this questionnaire is described as follows.

Questionnaire for RehaBio Rehabilitation System

Subject ID: _________________________ Age: _______ Date: _____________

Please respond to the following survey questions according to the scale 1 to 4, where 4 represents strongly agree and 1 represents strongly disagree.

1. I have tried augmented reality games before.

1 **2** **3** **4**

2. The game is motivated and interested.

1 **2** **3** **4**

3. The given information and guide are easy to understand.

1 2 3 4

4. It is comfortable to wear the marker.

1 2 3 4

5. The present of feedback such as timer and scoring system are motivating.

1 2 3 4

6. Tracking of the colour marker is good.

1 2 3 4

7. It can feel the arm muscles fatigue.

1 2 3 4

8. It is comfortable throughout the exercise.

1 2 3 4

9. The training duration for healthy/stroke user is appropriate.

1 **2** **3** **4**

10. Please provide other feedbacks and suggestions if any.

A.3.2 ARIS System

There are two questionnaires in ARIS system. Questionnaire A is conducted in order to evaluate the user's ownership illusion feeling whereas Questionnaire B is conducted for the subject's feeling during performing the rehabilitation exercise with ARIS system.

A.3.2.1 ARIS Questionnaire A

Questionnaire A: Ownership Illusion

Subject ID: ________________________ Age: _______ Date: _____________

Please respond to the following survey questions according to the scale 1 to 4, where 4 represents strongly agree and 1 represents strongly disagree.

1. Real arm moves due to virtual arm.

1 **2** **3** **4**

2. I feel like synchronized between real arm and virtual arm.

1 **2** **3** **4**

3. I feel like picking the object with real arm.

1 **2** **3** **4**

4. I feel like virtual arm as my real arm.

1 **2** **3** **4**

5. It is a good illusion environment.

1 **2** **3** **4**

6. Please provide other feedbacks and suggestions if any.

A.3.2.2 ARIS Questionnaire B

Questionnaire B: ARIS rehabilitation System

Subject ID: __________________________ Age: ________ Date: ______________

Please respond to the following survey questions according to the scale 1 to 4, where 4 represents strongly agree and 1 represents strongly disagree.

1. I have Augmented Reality / Video Games experience.

1 2 3 4

2. The Graphical User Interface (GUI) is user-friendly and easy to adapt.

1 2 3 4

3. AIRS provide with enough information such as current hand position and joint angles.

1 2 3 4

4. During the training phase, I received enough information and training sessions.

1 2 3 4

5. The multiple colors tracking in ARIS is good.

1 2 3 4

6. ARIS is easy to understand and manipulate.

1 **2** **3** **4**

7. ARIS can detect the threshold level of my sEMG signal (Threshold Mode).

1 **2** **3** **4**

8. When my arm move, the VHA model was move accordingly (Prediction Mode).

1 **2** **3** **4**

9. During training and testing phase, I felt that my upper limb muscles were fatigue.

1 **2** **3** **4**

10. The immediate feedbacks such as real-time trajectory tracking, threshold level, hand position and joint angles are very good and useful.

1 **2** **3** **4**

11. As a whole, the ARIS is interesting, motivating and enjoyable.




1 **2** **3** **4**

12. Suggestion and improvements are welcome.

A.4 Ethical Approval

The ethical approval was attained to collect the EMG data for the purpose of this research. The reference number for clearance is UTS HREC REF NO. 2009-181A.

A.5 Email Communication with Dr. Geoffrey Murray (Port Kembla Hospital)

From: Adel Ali Al-Jumaily
Sent: Friday, 11 December 2015 10:57 AM
To: Geoffrey Murray
Subject: Re: Robotic assisted uper extremity rehab for post-stroke patients - HE14/400
Hi Geoff,
I am going to submit application in our University and update you.
Regards.
Adel
On 10/12/2015 1:35 am, "Geoffrey Murray" <Geoffrey.Murray@SESIAHS.HEALTH.NSW.GOV.AU>
wrote:
>
>Hi Adel,
>
>We share the Ethics committee with UOW. If UTS Ethics approve it is a formality which I think I can take care of.
>
>Regards,
>
>Geoff.
>____
>From: Adel Ali Al-Jumaily [Adel.Al-Jumaily@uts.edu.au]
>Sent: Wednesday, 9 December 2015 5:35 PM
>To: Geoffrey Murray
>Cc: 'Yee Aung ([redacted])'

>Subject: RE: Robotic assisted uper extremity rehab for post-stroke
>patients - HE14/400
>
>Hi Geoffrey,
>Thanks for your e-mail, I will take care about the University ethical approval. I have many ethical approvals for
different projects.
>I am just wandering if any ethical approval required for the hospital.
>Regards.
>Adel
>
>
>Dr. Adel Al-Jumaily
>Associate Professor,
>Faculty of Engineering and IT
>University of Technology, Sydney
>City campus,
>Building 11, level 9, Room 116
>T +61 2 9514 7939
>F +61 2 9514 2655
>Address: PO Box 123 Broadway NSW 2007 Australia
>Adel UTS Web Link 1, Adel Web Site link 2
>
>-----Original Message-----
>From: Geoffrey Murray
2
>[mailto:Geoffrey.Murray@SESIAHS.HEALTH.NSW.GOV.AU]
>Sent: Friday, 4 December 2015 4:54 AM
>To: Adel Ali Al-Jumaily
>Subject: RE: Robotic assisted uper extremity rehab for post-stroke
>patients - HE14/400
>
>
>Hi Adel,
>
>Sorry but I didn't read your email properly. You will need to put a proposal to the Ethics Committee at your
university before we can do anything. Essentially you need to convince them that you will do no harm by
experimenting on human subjects. UTS would have an Ethics Department who can provide you with advice.
>
>Regards,
>
>Geoff.
>____
>From: Adel Ali Al-Jumaily [Adel.Al-Jumaily@uts.edu.au]
>Sent: Tuesday, 1 December 2015 11:55 AM
>To: Geoffrey Murray
>Subject: FW: Robotic assisted uper extremity rehab for post-stroke
>patients - HE14/400
>

>Dear Geoff,
>I hope you are fine and doing well, I sent you the included e-mail on 16 October regarding the test of the system in
hospital.
>Would you, please, inform me about any update.
>Kind Regards.
>Adel
>
>Dr. Adel Al-Jumaily
>Associate Professor,
>Faculty of Engineering and IT
>University of Technology, Sydney
>City campus,
>Building 11, level 9, Room 116
>T +61 2 9514 7939
>F +61 2 9514 2655
>Address: PO Box 123 Broadway NSW 2007 Australia
>Adel UTS Web
Link<http://datasearch2.uts.edu.au/feit/staff/listing/details.cfm?StaffId=6770#tab4> 1, Adel Web Site link 2<http://services.eng.uts.edu.au/~adel/index.htm>
>
>From: Adel Ali Al-Jumaily
>Sent: Friday, 16 October 2015 12:10 PM
>To: 'Geoffrey Murray'
>Subject: RE: Robotic assisted uper extremity rehab for post-stroke
>patients - HE14/400
>
>Dear Geoff,
>Thanks for instant response.
>We want to do a study in a hospital setting and have no problem to compare AR + usual treatment compared with
usual treatment and measure differences.
>About your suggestion to study patients after their usual therapy is completed in an outpatient setting; we are
fixable and happy to do that and no problem to run the pilot study.
>Regarding my expectations from AR based treatment use, it will make more motivation, fast recovery, minimum
supervision, and can be used in or out of hospital (home).
3
>Please advise me how we can start.
>Regards.
>Adel
>
>
>Dr. Adel Al-Jumaily
>Associate Professor,
>Faculty of Engineering and IT
>University of Technology, Sydney
>City campus,
>Building 11, level 9, Room 116
>T +61 2 9514 7939
>F +61 2 9514 2655

>Address: PO Box 123 Broadway NSW 2007 Australia
>Adel UTS Web
Link<http://datasearch2.uts.edu.au/feit/staff/listing/details.cfm?StaffId=6770#tab4> 1, Adel Web Site link 2<http://services.eng.uts.edu.au/~adel/index.htm>
>
>From: Geoffrey Murray
>[mailto:Geoffrey.Murray@SESIAHS.HEALTH.NSW.GOV.AU]
>Sent: Tuesday, 13 October 2015 2:04 PM
>To: Adel Ali Al-Jumaily
>Subject: RE: Robotic assisted uper extremity rehab for post-stroke
>patients - HE14/400
>
>Hi Adel,
>
>If you are going to do a study in a hospital setting, you would not get Ethics approval if you wanted to study AR
compared to usual treatment. You would have to compare AR + usual treatment compared with usual treatment
and measure differences.
>
>I would suggest you study patients after their usual therapy is completed in an outpatient setting. Obviously you
would start with a pilot to perfect your intervention with AR, and then presumably you would do a comparative
study comparing AR with no treatment (stroke patients do improve over time without therapy) Ideally the
participants would be randomized. Your participant size would depend on measureable change you detect in your
pilot. There are potential validated instruments that you could use to measure change in upper limb function, but I
would need to know more about what your expectations from the AR are before I could advise you on the most
appropriate.
>
>Regards,
>
>Geoff.
>
>From: Adel Ali Al-Jumaily [mailto:Adel.Al-Jumaily@uts.edu.au]
>Sent: Tuesday, 13 October 2015 11:14 AM
>To: Geoffrey Murray
><Geoffrey.Murray@SESIAHS.HEALTH.NSW.GOV.AU<mailto:Geoffrey.Murray@SESIA
>HS.HEALTH.NSW.GOV.AU>>
>Cc: 'Yee Aung
>(Yee.M.Aung@student.uts.edu.au<>)'
><Yee.M.Aung@student.uts.edu.au<>>
>Subject: RE: Robotic assisted uper extremity rehab for post-stroke
>patients - HE14/400
>
>Dear Geoff,
>It was nice to meet you and delivery our presentation.
4

>As we discussed about the next step of the clinical trail and implementation, I attached draft what we think to start
with.
>Hope to receive your feedback to plan for our further steps.
>Regards.
>Adel
>
>Dr. Adel Al-Jumaily
>Associate Professor,
>Faculty of Engineering and IT
>University of Technology, Sydney
>City campus,
>Building 11, level 9, Room 116
>T +61 2 9514 7939
>F +61 2 9514 2655
>Address: PO Box 123 Broadway NSW 2007 Australia
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Link<http://datasearch2.uts.edu.au/feit/staff/listing/details.cfm?StaffId=6770#tab4> 1, Adel Web Site link 2<http://services.eng.uts.edu.au/~adel/index.htm>
>
>From: Geoffrey Murray
>[mailto:Geoffrey.Murray@SESIAHS.HEALTH.NSW.GOV.AU]
>Sent: Wednesday, 2 September 2015 4:35 PM
>To: David Stirling; Fazel Naghdy; Adel Ali Al-Jumaily
>Cc: Haiping Du; maj890@uowmail.edu.au<mailto:maj890@uowmail.edu.au>;
>xh962@uowmail.edu.au<mailto:xh962@uowmail.edu.au>; Maryam Ghahramani;
>Sina Ameli; Paul Stapley; Maren Jones; David Rollestone; Namuk
>Alkhateeb; Tanya Woll
>Subject: RE: Robotic assisted uper extremity rehab for post-stroke
>patients - HE14/400
>
>Hi David and Adel,
>
>It looks as though 24/9/15 between 3 pm and 5 pm is doable for everyone. We will send instructions on how to get
here.
>
>Xianwei from UOW will demonstrate his robotic Amadeo finger rehab unit and Assoc Prof . Adel Al-Jumaily and
team from UTS will demonstrate their Augmented Reality (AR) based upper limb rehabilitation exercises for stroke
patients. Possibly Mitchell from UOW will also demonstrate virtual reality research that he is doing. We will make up
a publicity flyer when we know whether Mitchell can participate.
>
>We will book the physio gym, and I will invite physiotherapists and occupational therapists, as well as rehab
doctors, to attend. I will also see if John Carmody (neurologist) is free to attend.
>
>I think there could be a relatively large attendance (guesstimate about 30). It will be in the physiotherapy gym at
the hospital.

>
>I would think for you guys seeing what each other is doing would be very useful, and I hope we can collectively
have some useful clinical input/suggestions in to your research.
>
>Looking forward to your presentations and many thanks,
>
>Geoff.

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