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*Multi-mode Stroke Rehabilitation System
Using Signal-Controlled Human Machine Interface*

Kairui Guo

School of Biomedical Engineering
Faculty of Engineering and Information Technology
University of Technology Sydney
NSW - 2007, Australia

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Using Signal-Controlled Human Machine Interface

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Kairui Guo

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ABSTRACT

Stroke has become one of the most devastating health problems due to post-stroke disabilities. Rehabilitation is the necessary process for stroke survivors following discharging from the intensive care units. Of those stroke survivors, 82% of them cannot regain full arm functions, in turn, their daily lives are dramatically affected since they cannot perform daily activities such as eating, dressing, or taking showers independently. In recent years, technology-assisted rehabilitation is introduced using functional electrical stimulation, robotic devices, and virtual reality. Although technology-based systems have demonstrated advantages in early research, there are numerous aspects needed to be further investigated to ensure more stable physiological analysis of the affected upper limb and broader usage in the clinical field.

This thesis proposes a complete upper-limb rehabilitation system with multimodal motor function training using neuroelectric signals. First, motion intent recognition and emotion classification is analysed using electroencephalogram (EEG) signal. The EEG-based motion intent recognises the desired motion of stroke patients before the motion is executed. At the same time, emotions of the patients are monitored to ensure safety while the patients are doing exercises. Novel designed classifiers, including hybrid Support Vector Machine and hidden Markov Model and a Fuzzy-based Support Vector Machine, are demonstrated. The EEG-based classifiers are able to achieve 78% accuracy using novel machine learning algorithms, which improves 10-15% comparing with the classical methods.

Second, electromyography (EMG) is one of the most frequently used parameters since it reveals the electrical activity of a specific muscle that is related to the muscle force. In this thesis, EMG connectivity analysis using multivariable autoregression is proposed to analyse the inter-relationship between muscles. Using EMG connectivity analysis, the paretic arm is considered as the abnormal system, and the non-paretic arm is the reference side. The rehabilitation strategy is to control the abnormal system to generate identical EMG connectivity patterns as the reference side.

After integrating the layers controlled by physiological signals, a wearable exoskeleton is built as a rehabilitation device by mimicking human-like movements. The exoskeleton guides and supports rehabilitation movements based on the patients' physiological signals. After consolidating with physiotherapists and stroke patients, features such as wireless communication, low-power consumption, touch screen user interface, etc., are implemented to promote the ease-of-use and expand the possible applications in the clinical field. At the moment, a clinical study that has recruited nine stroke patients is

conducted regarding outcome assessment and rehabilitation prediction. Followed by this study, the developed exoskeleton will be evaluated on stroke patients.

AUTHOR'S DECLARATION

I, *Kairui Guo* declare that this thesis, submitted in partial fulfilment of the requirements for the award of Doctor of Philosophy, in the *School of Biomedical Engineering, Faculty of Engineering and Information Technology* at the University of Technology Sydney, Australia, is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution. This research is supported by the Australian Government Research Training Program.

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PLACE: Sydney, Australia

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LIST OF PUBLICATIONS AND AWARDS

PUBLICATIONS :

1. K. Guo, et al., 'EEG-based Emotion Classification Using Innovative Features and Combined SVM and HMM Classifier', IEEE EMBC 2017. (Chapter 2)
2. K. Guo, et al., 'EMG-Based Robot-Assisted Stroke Rehabilitation For Upper-limb Impairment,' ABEC 2018, Australia, 2018, p. 9. (Chapter 3)
3. K. Guo, et al., 'A Hybrid Fuzzy Cognitive Map / Support Vector Machine Approach for EEG-based Emotion Classification Using Compressed Sensing', International Journal of Fuzzy Systems, S.I.: Fuzzy System Big Data Mining, 2019. (Chapter 2)
4. K. Guo, et al., 'A Hybrid Physiological Approach of Emotional Reaction Detection Using Combined FCM and SVM Classifier', IEEE EMBC 2019. (Chapter 2)
5. K. Guo, et al., 'Puzzle-based Upper Limb Functional Electrical Stimulation Strategy Using EMG Connectivity Analysis', IEEE EMBC 2020. (Chapter 3)

AWARDS :

1. Lam Yuen Trust and ACETCA Medical Research Award at University of Technology Sydney in 2017
2. DST Group and UTS - Student Innovation Competition, Emerging Disruptive Technology Assessment Symposium 2017
3. UTS, FEIT HDR Collaboration Experience Award 2019
4. 2019 John Heine Memorial Foundation International PhD Prize
5. 2020 UTS Techcelerator, Most Feasible Prototype Award

TABLE OF CONTENTS

List of Publications	vii
List of Figures	xi
List of Tables	xv
1 Introduction and Literature Review	1
1.1 Introduction: Human Brain, Neural Signals and Measurements	2
1.1.1 Computed Tomography and Positron Emission Tomography	6
1.1.2 Magnetoencephalography	7
1.1.3 Magnetic Resonance Imaging and Functional Magnetic Resonance Imaging	8
1.1.4 Functional Near-infrared Spectroscopy	9
1.2 Electroencephalography	11
1.3 Electromyogram	15
1.4 Stroke Rehabilitation and Wearable Robotics	18
1.5 Overview of the Thesis	20
2 Emotion Recognition and Brain-Computer Interfaces	23
2.1 Introduction	23
2.2 Material	25
2.3 Solution One: novel parameter with combined support vector machine and hidden Markov model classifier	27
2.3.1 Methods	27
2.3.2 Results	30
2.4 Solution Two: hybrid fuzzy cognitive map / support vector machine using compressed sensing	32
2.4.1 Methods	32

TABLE OF CONTENTS

2.4.2	Results	36
2.5	Solution Three: joint EEG and facial expression features	41
2.5.1	Methods	41
2.5.2	Results	44
3	Electromyogram and Post Stroke Movement Analysis	49
3.1	sEMG-based Statistic and Frequency Analysis	49
3.2	EMG Connectivity Analysis in Stroke Rehabilitation	51
3.2.1	Materials	52
3.2.2	EMG Connectivity Analysis	53
3.2.3	Graph Theory Analysis	55
3.2.4	Discussion	56
3.3	An EMG Connectivity Application: Functional Electrical Stimulation- based Stroke Rehabilitation System	58
3.3.1	Introduction	58
3.3.2	Methods	59
3.3.3	Results and Discussion	60
3.4	Conclusion	63
4	Hybrid Biosignal-based Rehabilitation System Using A Wearable Robot	65
4.1	AI Exoskeleton: a Self-developed Rehabilitation Robot	65
4.2	Virtual Reality-based Motor Imagery	70
4.3	Human-Machine Interface: Upper Limb Movement Prediction	75
4.4	Fatigue and Safety: an Application for Emotion Classification	76
4.5	A Clinical study: EMG analysis and Upper Limb Fugl-Meyer Assessment	77
4.5.1	Intruduction	77
4.5.2	Experimental Protocol	78
4.5.3	Results and Discussion	79
4.6	Conclusion	93
5	Summary and Future Work	95
5.1	Summary	95
5.2	Future Work	97
A	Appendix	99
	Bibliography	101

LIST OF FIGURES

FIGURE	Page
1.1 The anatomic planes of the human brain	3
1.2 Lobes of the human brain and their functions	3
1.3 The limbic system of the human brain	4
1.4 The motor cortex of the human brain	5
1.5 An example of a computed tomography machine	6
1.6 CT (left) and PET/CT (right) images of the human brain	7
1.7 An example of the MEG machine	7
1.8 MEG scan images of the human brain	8
1.9 An overview of the MRI system	9
1.10 An fNIRS image showing the oxygenated and deoxygenated haemoglobin levels	10
1.11 An example of fNIRS used in a stroke-related clinical study	10
1.12 The cycle of a neuron's membrane potential	11
1.13 The international 10-20 system for EEG sensor placement	12
1.14 Examples of BCI Applications	14
1.15 A schematic representation of motor control mechanisms	15
1.16 An example of needle EMG	16
1.17 A summary of this thesis	20
2.1 2D Emotion Planes	26
2.2 Functional Block Diagram	27
2.3 Valence Plane Classification Accuracy: all 32 participants are demonstrated on the x-axis. The y-axis indicates the classification accuracy in decimal numbers. The yellow dash line represents the traditional SVM classification, and the blue solid line is accuracy for the novel combined SVM and HMM classifier.	30

LIST OF FIGURES

2.4 Arousal Plane Classification Accuracy: all 32 participants are demonstrated on the x-axis. The y-axis indicates the classification accuracy in decimal numbers. The green dash line represents the traditional SVM classification, and the red solid line is accuracy for the novel combined SVM and HMM classifier. 31

2.5 Average Accuracy: SVM vs Combined Classifier 32

2.6 An example of Fuzzy Cognitive Map 33

2.7 Functional Block Diagram 34

2.8 Hybrid SVM & FCM Classifier. First two features are relative wavelet energy and relative wavelet entropy, entering the SVM classifier. The output of the SVM classifier together with these two feature establish the FCM, which presents the final output of the classified emotions. 36

2.9 A Segment of EEG and its recovered signal from CS 36

2.10 Accuracy on Valence-Arousal Plane 38

2.11 Accuracy on Dominance-Liking Plane 39

2.12 Average Accuracy with standard deviation on four Emotion Planes. Blue bar represents classical SVM classifier. Red bar represents hybrid SVM and FCM classifier using epoch. Yellow bar represents hybrid SVM and FCM classifier using video. 40

2.13 Emotion Model: Negative Neutral Positive 41

2.14 Functional block diagram. 42

2.15 The sample facial image after auto-screenshot from the videos. 43

2.16 Examples of texture primitives which can be detected by LBP (white circles represent ones and black circles zeros). 44

2.17 Accuracy on Valence Plane 45

2.18 Accuracy on Arousal Plane 45

2.19 Accuracy on ‘Negative Neutral Positive’ Plane 46

2.20 Average Accuracy on Three Different Emotional Planes. Yellow indicates valence, and green indicates arousal plane. The blue bars use the NNP model. 47

3.1 An Example of 8-puzzle Problem 59

3.2 Patient 9 Non-paretic Sides 25% MGF DTF Representation Using 8x8 Matrix 60

3.3 Patient 9 Paretic Sides 25% MGF DTF Representation Using 8x8 Matrix . . . 61

3.4 Permutation Format: Three-dimensional Human Model 62

3.5 8-Puzzle Solver 62

4.1	AI Exoskeleton	67
4.2	Hand section of the AI Exoskeleton	68
4.3	AI Exoskeleton performing pinch grip	68
4.4	AI Exoskeleton holding a cup	69
4.5	AI Exoskeleton: wrist and forearm with actuators	69
4.6	AI Exoskeleton: elbow, upper arm and shoulder with actuators	70
4.7	EEG sensor placement (in red) for MI experiment	71
4.8	Timeline for the ME/MI trial	72
4.9	An example of the visual cue: a computer-based movement instruction	72
4.10	VR-based movement instruction: drinking water from a cup	73
4.11	EMG sensor location for the EMG-FMA experiment	78
4.12	Patient 1 FMA score. Category 1 (C1) is volitional movement within synergies (flexor) in navy. Category 2 (C1) is volitional movement within synergies (extensor) in organe. Category 3 (C1) is volitional movement mixing synergies in yellow. Category 4 (C1) is volitional movement within little or no synergies in purple. Category 5 (C1) includes movements on wrists in green. Category 6 (C1) are motions related to hands in blue. Category 7 (C1) is coordination and speed in maroon.	80
4.13	Patient 1 Movement 12 EMG Analysis	81
4.14	Patient 1 Movement 28 Affected Side EMG Connectivity	81
4.15	Patient 1 Movement 28 Non-affected Side EMG Connectivity	82
4.16	Patient 2 FMA score	82
4.17	Patient 2 EMG Analysis for Movement 23	83
4.18	EMG Connectivity analysis on Movement 28. Affected Arm.	84
4.19	EMG Connectivity analysis on Movement 28. Non-affected Arm.	84
4.20	Patient 3 FMA score	85
4.21	Patient 3 Movement 2 EMG Analysis	86
4.22	EMG Connectivity analysis on Movement 21. Affected Arm Week 3.	86
4.23	EMG Connectivity analysis on Movement 21. Affected Arm Week 4.	87
4.24	EMG Connectivity analysis on Movement 21. Non-affected Arm Week 4.	87
4.25	Patient 4 FMA score	88
4.26	Patient 4 Movement 17 EMG Analysis	89
4.27	Patient 5 FMA score	89
4.28	EMG Connectivity analysis on Movement 19. Affected Arm Week 1.	90
4.29	EMG Connectivity analysis on Movement 19. Affected Arm Week 2.	91

LIST OF FIGURES

4.30	EMG Connectivity analysis on Movement 19. Affected Arm Week 3.	91
4.31	EMG Connectivity analysis on Movement 19. Affected Arm Week 4.	92
4.32	EMG Connectivity analysis on Movement 19. Non-affected Arm Week 4. . . .	92

LIST OF TABLES

TABLE	Page
2.1 average accuracy for different feature combinations	30
2.2 Confusion matrix for the three designed classifiers	40
3.1 Permutation Format: Cycle Notation	61

