University of Technology Sydney

Faculty of Engineering & Information Technology

Modelling, Regulating and Controlling Cardiovascular Responses by using Wearable Sensors

A thesis submitted for degree of

Doctor of Philosophy

Hamzah AlQudah

Certificate

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 part of the collaborative doctoral degree and/or 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. *This research is supported by the Australian Government Research Training Program Scholarship.*

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List of Abbreviation

μ-IMU	Micro Inertial Measurement Units
ACSM	American College of Sports Medicine
ADC	Analog Digital Convertor
ADP	Adenosine Diphosphate
ARC	Automatic Memory Counting
ATP	Adenosine triphosphate
BLE	Bluetooth Low Energy
BP	Blood Pressure
bpm	beats per minute
CCS	Code Compose Studio
CO_2	Carbon Dioxide
Cr	Creatine
CR	Cardiac rehabilitation
CRPs	Cardiac Rehabilitation Programs
CU	Charging Unit
ECG	Electrocardiogram
GPS	Global Positioning System
HR	Heart Rate
HR_{max}	Maximum Heart Rate
HR_{reseve}	Reserved Heart Rate
HR_{rest}	Rest Heart Rate
IDE	Integrated Development Environment
IDF	International Diabetes Federation
IMU	Inertial Measurements Unit
IR	Impulse Response
LED	Light Emitting Diode
LTI	Linear Time Invariant
MCU	Micro Controller Unit
MET	Metabolic Equivalent
MSB	Most Significant Bit

N_2	Nitrogen
O_2	Oxygen
PCr	Phosphocreatine
Pi	inorganic Phosphate
Psi	Pounds per Square Inch
PU	Portable Unit
RKHS	Reproducing Kernel Hilbert Space
RMS	Root of Mean Square
RQ	Respiratory Quotient
SC	Serial Clock
SD	Serial Data
SISO	Single Input Single Output
SMD	Surface Mounted Devices
SS	Stable Spline
TA	Tri-axial Accelerometer
TCA	Tri-Carboxylic Acid
TI	Texas Instruments
UART	Universal Asynchronous Receiver Transmitter
USB	Universal Serial Bus
USCI	Universal Serial Communication Interface
VCO_2	Volume of Carbon Dioxide
VE	Ventilation
VO_2	Oxygen Uptake
VO_2max	Maximum Oxygen Uptake
VT	Ventilatory Threshold

Abstract

Physical exercise has significant benefits for humans in improving the health and quality of their lives, by strengthening the functions of their cardiovascular and respiratory systems. However, it is very important to control the intensity of the exercise within the capability of the individual to maximize the efficiency of the exercise and ensure the safety of the exercises.

The maximal rate of oxygen uptake (VO_{2max}) and Heart Rate (HR) are the important determinants of cardiovascular fitness and health status; their measurements can help in cardiac diseases detection.

In this thesis, we first developed two reliable and valid wearable exercise monitoring systems by using TI e Z430-Chronos watch as well as iPhone App, which can control the exercise intensity through audio stimulations and audio command to improve cardiovascular fitness of various exercisers.

Various exercises including treadmill exercise and stair climbing were performed under the monitoring and controlling of the developed wearable devices together with the portable gas analyzer, $K4b^2$. Based on experimental data, we applied the non-parametric model to investigate the dynamics of Heart Rate (HR) response to stairs exercise status. The self-designed application provides a reliable technique to record HR data and to present safe and understandable exercise instructions. The protocol of the experiment guarantees a continuously monitoring of HR. The identification result of different period numbers are compared, and the models, which includes three types of parametric models and one nonparametric model, are also presented.

In conclusion, the developed portable monitoring systems, exercise protocols, and HR models have great potential to accurately predict and regulate the dynamic cardiorespiratory response to moderate strength exercise, promote safer exercise and guide the cardiac patient's during the outpatient cardiac rehabilitation phase.

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Chapter 1 : INTRODUCTION

1.1 Background

Regular exercises and physical activities are very important in maintaining human being health; many diseases can be avoided by just exercising regularly. Utilizing treadmill as an indoor training environment or climbing stairs as an example of an outdoor exercise environment are an excellent means to maintain the human body health and strengthening the cardiovascular health and fitness. However, to guarantee overall health improvement and to protect the exerciser from any injury, it is of great interest to monitor, regulate, and control the exercise intensity and load.

The maximal rate of oxygen uptake (VO_{2max}) and Heart Rate (HR) are the important determinants of cardiovascular fitness and health status; their measurements can help in cardiac diseases detection.

The American College of Sports Medicine's (ACSM) guidelines has prescribed exercise intensity for developing and maintaining the cardiorespiratory fitness for adults. It suggests performing at 70%-94% of the maximum heart rate to achieve the desired cardiovascular fitness targets. However, [1] has recommended 80% of the maximum heart rate for unfit people and those with respiratory or cardiac risks.

The measurement of oxygen uptake during sport or other outdoor activities is of great interest for the development of training programs and the study of their effects on elite athletes or for assessing the efficacy of rehabilitation therapy.

In recent years, wearable sensors have achieved a potential development that makes them cost-effective, easily available and reliable. These developments encourage researchers to integrate them in many clinical applications such as cardiovascular, neurological, asthmatic, and hypertensive diseases [2, 3].

Further, there are concerns regarding the performance of wearable sensors in healthcare monitoring systems. These concerns include (1) failing to use real-time data in monitoring systems during testing of application, (2) battery issues, (3) security and privacy of the data collected from patients, (4) requirement of medical professional's recommendations at each step of the development, (5) clinical validation or experts' acceptance, and (6) user-friendliness for patients and healthcare professionals [4].

In this study, we propose a home-based monitoring system to monitor and regulate exercise intensity and guide patients' through the duration of their exercises. The collected data can then be transferred to the specialist for further diagnosis and improvement of the exercise protocol. It is intended that this would guarantee the improvement of people's cardiovascular fitness.

In this study, we use a wearable low-cost device to monitor heart rate that is suitable for remote and home-monitoring applications. At present, dozens of wearable models are available in the market that can measure the heartbeat rate at rest as well as during walking and running, by means of optical sensors, gyroscopes, accelerometers, and pressure sensors embedded in the wearables. These commercial devices are as effective as the expensive beat-to-beat blood pressure devices, which are used in hospital environments.

In this work, we set out to learn the individual characteristics of cardiovascular responses by observing the relationship between physical activity and associated changes in heart rate in everyday life. Heart rate monitoring is important for reducing healthcare access problems and associated costs.

During a single training session, a person's HR response can fluctuate due to internal (i.e., training status, genetics, mood) and external (i.e., environmental conditions, nutrition, water supply) factors. A high variation of longer and shorter heart cycles can be observed by recording every single heartbeat. It is necessary to obtain a person's optimal cardiovascular responses with respect to exercises. Therefore, modelling is needed in practice to predict individual responses.

In this study, we have implemented the training and rehabilitation control system on a smart mobile device and an eZ430-Chronos watch. The smartphone is used by many people nowadays. Due to their complexity and the difficulty for some older people or patients to use them, the control system is implemented on an eZ430-Chronos watch which is small, inexpensive and user-friendly.

Our research interests focus on new technologies and devices to monitor, evaluate, and control human cardiovascular and respiratory responses for safe and effective exercise and rehabilitation under free-living conditions.

The remainder of this section is organized as follows. The objectives and aims of the study are presented in Section 1.2. Section 1.3 explains the modelling problems in cardiovascular responses to exercise. Contributions are in Section 1.4. Publications are listed in Section 1.5, and the overall structure of this thesis is outlined in Section 1.6.

1.2 Research Objective

Currently, both invasive and non-invasive biomedical measurements are rapidly being developed. However, an invasive device is usually considered to have a higher potential hazard than an equivalent non-invasive device [5]. In human exercise responses and related areas, the approach to non-invasive measurement is considered more preferable to invasive measurement, due to the specific circumstances whereby the users only use non-invasive devices with their daily exercise.

Another important performance taken into account is a device's portability. Continuous measurement of key cardiovascular responses, such as heart rate (HR) and oxygen consumption (VO_2) for outdoor exercise poses an important and very challenging problem, as most existing equipment for measuring these variables is only suitable for indoor exercise monitoring because of size, weight, and mobility limitations. We aim to develop a sophisticated wearable portable sensor network, which can wirelessly monitor key cardiovascular variables to both indoor and outdoor exercise under free-living conditions.

In addition, the fundamental difficulty of this study is the modelling and control of cardiovascular responses from non-invasive measured parameters. In this study, we have developed model-based control systems in terms of single-input single-output (SISO) frameworks. Within the SISO closed-loop control framework, a control-oriented modelling approach using the nonparametric method is presented. Based on that, a novel control algorithm has been developed for monitoring and thus, the regulation of exercise intensity.

Describing in more details the purpose of this study, there are a number of aims as follows:

1. Develop and build a nonparametric model based on the kernel-based impulse response estimation, which can accommodate different exercises' data such as use treadmill and stair climbing.

2. Develop a movement algorithm. The algorithm utilizes built-in sensors such as an accelerometer, a gyroscope and a barometer to detect any movement and identify the movement type and parameters such as speed, steps, pace and direction. The algorithm's voice, audio commands and notifications guide the user throughout the exercise. This novel and an innovative algorithm is intended for safe and effective exercise and rehabilitation under free-living conditions.

3. To identify the dynamic system responses under various exercise conditions, the experimental approach was applied to investigate human cardiovascular responses at both a high and low intensity. In this research, twenty subjects performed a stair ascending and descending exercise for twelve minutes. During that exercise, HR, VO_2, steps and direction values were collected and recorded by the Cosmed $K4b^2$ device, Apple iPhone smartphone, and TI eZ430-Chronos watch. The identification results of different period numbers were compared, and the transfer function model, which includes three types of system order, was also implemented for comparison purpose. The impulse response from the non- parametric model was more flexible, ensuring that a slight change of HR could be identified and then estimated. For each participant, the optimal fitness level of estimated HR was obtained through a different order of transfer function models.

4. To investigate the self-designed micro-IMU modelling approaches. The calibration approaches of the self-designed micro-IMU using different methods were explored. The classical calibration method achieves relatively higher accuracy than the auto-calibration method. As a result, we recommend a classic calibration method; if an accurate turntable is available, the classical calibration method should always be the first choice.

5. To implement the interval training protocol, which requires the participant to switch between high intensity and low intensity exercise in order to strengthening the human being cardiovascular fitness system and act as a part of the cardiac outpatients' phase.

6. Develop an iPhone application for monitoring and regulation of outdoor exercise. This study develops an iPhone application to estimate the human heart rate to suite a predefined exercise protocol and assist people to regulate exercise strength under the outdoor exercise environment. During exercise, a portable Polar Bluetooth HR chest strap is utilized to monitor the HR dynamics. In order to obtain the real-time HR data, the developed iPhone application is paired and connected with the Polar HR sensor with Bluetooth Low Energy, while developing a boundary control method for regulation of exercise intensity following the predefined exercise protocol, and an auditory system for exercise guidance.

7. Deploy the nonparametric model and the interval training protocol as a cardiac rehabilitation and control system on the eZ430-Chronos watch. The watch which is easy to use and inexpensive can guide cardiac patients during their cardiac rehabilitation phase. In the future, we plan to connect the system to iCloud to enable a cardiologist to monitor and review their patients' progress in recovery.

This research is implemented in real-life situations, and it shows promising results.

1.3 Problems in Modelling Cardiovascular Response to Exercise

The modelling of the human being biological signal has attracted many researchers in the last decade. Since [6], the modelling of the cardiovascular system parameters responses to exercise has been widely studied. Many studies for the modelling of the dynamics of the physiological response to treadmill exercise were also conducted [7, 8]. Some classical methods such as least square, maximum likelihood and prediction error methods could apply to linear system identification about HR signal responses to the exercise status.

However, the accuracy of identification results using these traditional methods is not satisfactory due to the insufficient stimulation [9, 10, 11]. When the prior information is not enough to determine the structure of the system, the nonparametric modelling method is a better choice [12, 13]. This method has been applied with the kernel-based regularization approach [14, 15, 16] by several researchers. The nonparametric method achieves high accuracy and robustness in system identification when studying the dynamics of HR response to exercise status with a well-designed kernel strategy and regularization term.

1.4 Thesis Contributions

Firstly, this thesis developed two wearable exercise monitoring systems based on a TI eZ430 Chronos watch and an Apple iPhone, respectively. Within these wearable systems, several efficient real-time algorithms have been proposed. One of the major innovative algorithms is the proposed step detection algorithm, which is integrated with an accelerometer, barometer, and gyroscope to detect the participant's movement during walking, running or climbing stairs. Although the use of these devices (to develop a step detection algorithm) are extensively explored, its real-time implementation for safe and effective exercise and rehabilitation under free-living conditions are not well researched.

The second area of this research is to build a nonparametric model based on the kernel-based impulse response estimation which can well accommodate the experimental data by including a kernelled regularization term to depict the heart rate dynamical responses to various exercises such as running on a treadmill or climbing the stairs. The developed impulse response nonparametric model is more flexible and has higher prediction accuracy than the parametric models.

Another area of this research is the implementation of the training and rehabilitation control system based on the developed nonparametric model. The control system was implemented as an application on the Apple iPhone, and it targets athletes and untrained people. In addition, the control system was also implemented on a wearable, and cheap TI eZ430 Chronos watch that can be easily operated by patients or older people. This research is implemented in a real-life situation, and it showed promising results.

Finally, various real-time experiments have been performed. By using a portable gas analyzer, K4b^2, experimental data has been collected, and the effectiveness of the developed wearable monitoring/regularization systems together with the nonparametric model has been demonstrated.

1.5 Publications

[1] Hamzah Alqudah, Kai Cao, Steven Su, and Branko Celler. "*Maximal Oxygen Uptake Estimation While Climbing Stairs using Smart Phones*" in ABEC 2018, Australia.

[2] Hamzah Alqudah, Kai Cao, Tao Zhang, Azzam Haddad, Steven Su, Hung Nguyen, and Branko Celler. "*Cardiovascular Fitness Strengthening using Portable Device*" in EMBC 2016, IEEE.

[3] Kai Cao, Line Ye, Hamzah Alqudah, Jan Szymankski, Jing Zhou and Steven Su. "*Dynamical Estimation of Key Cardiac-respiratory Variables by Using Commercialized Wearable Sensors*" IASTED International Conference Telehealth and Assistive Technology (TAT2016).

[4] Hamzah Alqudah, Xiwei Cui, Lin Ye, Kai Cao, Jan Szymanski, Ying Guo, and Steven Su, *"Modelling of Tri-axial Accelerometers in a Self-designed Wearable Inertial Measurement Unit*," the 9th International Conference on Sensing Technology (ICST 2015), Auckland, New Zealand.

1.6 Thesis Layout

This section of the study shows the order of the topics, their importance and relationship to each other. This thesis is structured in 9 Chapters. The brief overview of cardiorespiratory system, exercise in biomedical applications, and diseases related to cardiovascular system are presented in Chapter 2, providing an insight into the background used to this study for dealing with the problems inherent in the exercise-related biomedical engineering field, such as metabolic energy process, cardiovascular fitness, exercise protocols, diseases and rehabilitation.

Chapter 3 gives a full description of the equipment and tools that have been used in this study. Starting with Cosmed $K4b^2$ device and finishing with the programming languages that were utilised to program the iPhone and the eZ430-Chronos watch.

Chapter 4 concentrates on the developed control systems, the movement detection algorithm, which has been integrated into the Apple iPhone, in this chapter; we also explore the SWIFT programming language and C++ that used for eZ430-Chronos watch system programming.

Chapter 5 concentrates on the subjects participated in the experiment sessions; Section 2 presents the characteristics of each subject. However, Section 3 and 4 provide the preparation procedures as well as the experiment protocol and location conditions. Experiments results are presented in Section 4.

Chapter 6 explores the modelling approaches of the micro IMU; the current calibration methods are explained in Section 2, while the experiments and the results have been explained in Section 3 and 4.

The wearable control system, which is based on the interval training protocol along with the developed controller, are all presented in Chapter 7. The developed system targets cardiac rehabilitation during the outpatients' phase.

Chapter 8 investigates the dynamic response of cardiovascular to exercise intensity and explains the current modelling approach, such as the first order; Section 4 explains the nonparametric modelling approach with regularized kernel. In addition, the system identification explained in details in Section 5. Finally, Chapter 9 presents the conclusions.

Chapter 2 : LITERATURE REVIEW

2.1 Background

Regular physical activity and exercise are important for human health. It reduces the risk of chronic diseases such as diabetes, cancer, heart problems and high blood pressure.

2.1 Exercise and Energy Systems

During the last four decades, inventors and scientists have presented many ideas based on different mechanisms to convert wave energy into electricity. There are approximately eighty–one different concepts under development for wave energy extraction [2]. However, they are all at an early stage of development compared to Solar PV which represented about 47 % of newly installed renewable power capacity in 2016, while the wind and hydropower contributed 34 % and 15.5 %, respectively [16].

$$ATP^{4-} + H_2O \rightarrow ADP^{3-} + HPO_4^{2-} + H^+ + \text{Energy} \qquad \text{Equation 2.1}$$

2.1.1 Phosphagen system

In this system, the stored muscle PCr (phosphocreatine) together with the ATP (adenosine triphosphate) is broken down into Cr (creatine) and Pi (inorganic phosphate) through enzymatic reactions, which then donate a phosphate to ADP (adenosine diphosphate) to resynthesize ATP. This is again broken down through enzymatic reactions to ADP and Pi release energy for muscular activity. This system is anaerobic in nature; it does not require the presence of oxygen to resynthesize ATP [24]. Since the amount of PCr and

ATP in the muscles is low, therefore, limited energy available for short-term high-intensity activities (~1 to 30s) for example, sprinting or weight lifting [25].

2.1.2 Glycolysis system

In this system, the carbohydrate, in the form of muscle glycogen (the stored form of glucose in muscles) or blood glucose is broken down into two molecules of pyruvate through a series of chemical reactions and produced two molecules of usable ATP.

During glycolysis (Figure 2.1), glycogen is first converted into glucose-6-phosphate from glycogenolysis where it provides a source of fuel that degrades glucose-6-phosphate to pyruvate through a series of reactions [22]. This system provides energy to regenerate ATP during exercise longer than few seconds.

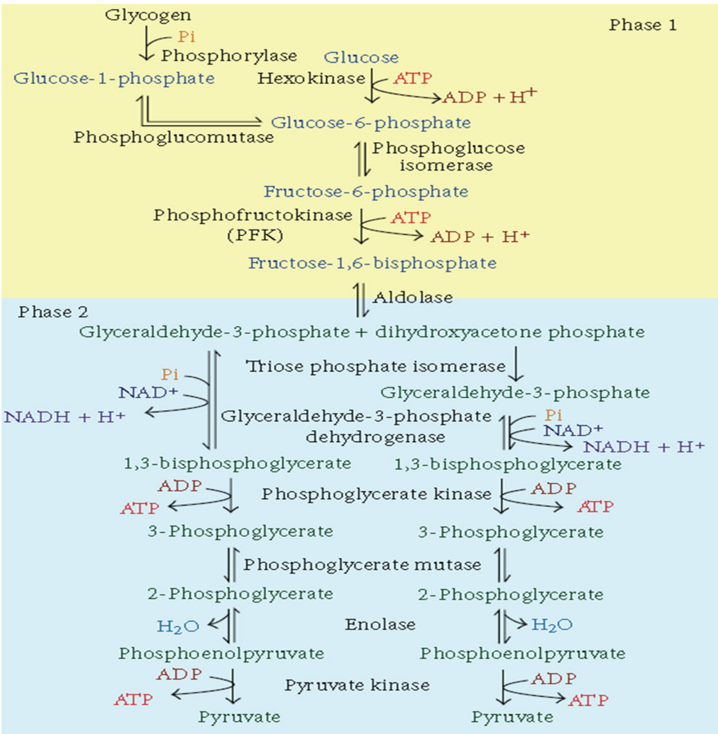


Figure 2.1: The glycolytic pathway. Adapted from [22]

The glycolysis system is the second fastest system to regenerate ATP and produce ATP quickly and suitable for activities that require large bursts of energy and lasts for a maximum of three minutes. During intense exercise, only a partial breakdown of glucose occurs called pyruvate [26]. Pyruvate production occurs at rates that exceed the capacity of the mitochondria to take up pyruvate; hence, conversion to lactate is essential for removing pyruvate to increase the rate of glycolytic ATP regeneration (Figure 2.2).

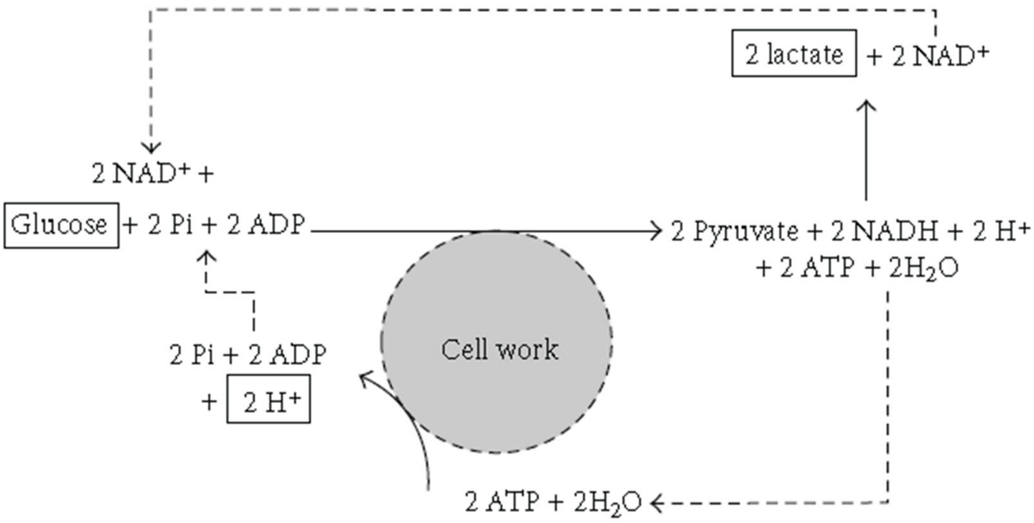


Figure 2.2: Lactate conversion in a glycolytic energy system. Adapted from [27]

2.1.3 Aerobic system

This system is also known as mitochondrial respiration. In the mitochondria the electron transport chain and the TCA (tri-carboxylic acid) or Krebs cycle generates more ATP by using blood glucose, free fatty acids and glycogen as fuels through the combustion and oxidized to CO_2 and water in the presence of oxygen. Initially, pyruvate produced through glycolysis is needed to convert acetyl-CoA, which enters Krebs cycle. This system is the slowest way that resynthesize ATP and can last for long term source of energy. This process takes approximately 40 to 90s to reach maximum level [24]. One molecule of glucose produces 36 molecules of ATP from the Krebs cycle and the electron transport chain through complete oxidation that produces 18 times as much ATP as anaerobic glycolysis [25]. To maintain intramuscular ATP concentration, these metabolic systems is continuously resynthesize ATP (Figure 2.3).

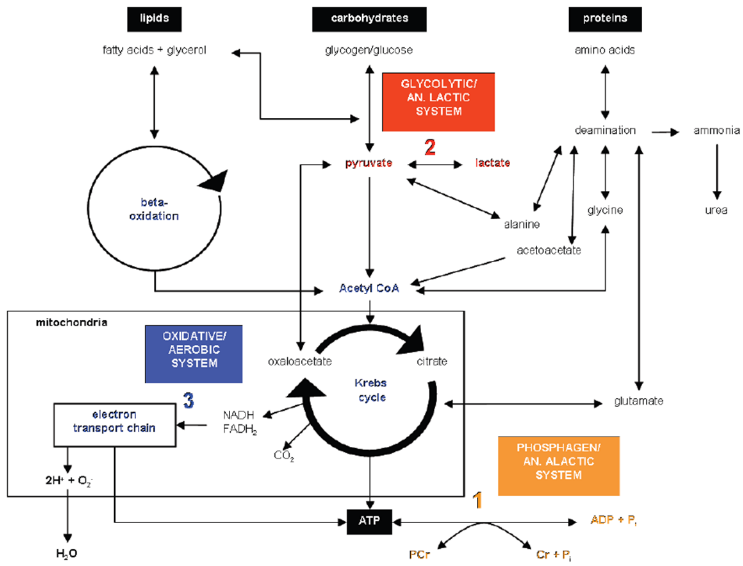


Figure 2.3: The three main metabolic energy pathways. Adapted from [24].

Fat in the form of triglycerides which is called intramuscular triglycerides (stored in adipose tissue underneath the skin within skeletal muscles) is the other primary sources of fuel for the aerobic system. It breaks down into free fatty acids and glycerol (a process called lipolysis). The fatty acids are transported to the muscle mitochondria where the carbon atoms are used to produce acetyl-CoA (a process called beta-oxidation) (Figure 3). Then fat metabolised like carbohydrate metabolism and enter in the Krebs cycle with acetyl-CoA and the electron transport chain transported electrons to create further ATP. The oxidation of glucose or glycogen produces less ATP than the oxidation of free fatty acids. The oxidation of one molecule of palmitate molecule (fatty acid) generates 129 molecules of ATP [25], [28].

2.2 Cardiovascular and respiratory systems

This section describes the essential components to understand the cardiovascular and respiratory systems. It explains heart, blood, blood vessels together with respiratory function. These systems carry oxygen to the muscles and different parts of the body during physical activity.

2.2.1 Cardiovascular system

The cardiovascular network is a closed loop system that circulate blood and the transport of oxygenated blood to the tissues and the de-oxygenated blood to the respiratory systems through various organs [29].

2.2.1.1 Heart and blood vessels

The heart is the pump that influence pressure to the blood to create the pressure gradient needed for blood to flow to the tissues [30]. It is hollow and cone-shaped. It is approximately the size of a closed fist and normally weighs between 148 to 296 g in women [31] and from 233 to 383 g in men [32]

The heart is divided into four compartments such as the right atrium, the left atrium, the right ventricle and the left ventricle (Figure 2.4). The upper chambers are called right and left atrium which receives blood returning to the heart and transfer it to the lower chambers called right and left ventricles which they pump out into the arteries. The left atria and ventricle are separated from the right atria and ventricle by septum. This prevents blood mixing from the two sides of the heart, because the left side of the heart receives and pumps oxygen-rich blood whereas the right side of the heart receives and pumps deoxygenated blood.

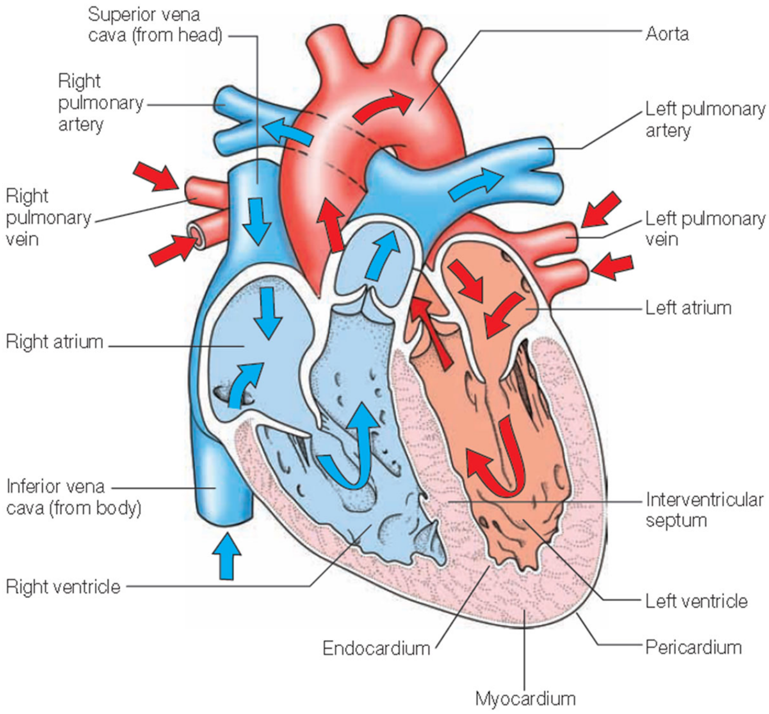


Figure 2.4: Blood flow through the heart. Adopted from [33].

Blood is the liquid medium within which materials being carried different parts in body, such as O_2, CO_2, nutrients, wastes, electrolytes, and hormones, including dissolved or suspended matter. It consists of watery plasma in which white blood cells, platelets and red blood cells are suspended [30].

The blood vessels are the passageways through which blood is directed to all part of the body and eventually back to the heart. The vessels systems are: the arteries which carry oxygenated blood from the heart to the organs; the veins which carry blood from the organs back into the heart; the capillaries are the smallest blood vessels between arteries and veins that distribute oxygen-rich blood to the organs [30].

2.2.1.2 Heart rate

Heart Rate (HR) is the number of contractions of the ventricles of the heart per minute and it is expressed as beats per minutes (bpm). It is the key indicator of functional health status. Any disorder in heartbeat is an aid early detection of disease in the heart [34]. The heartbeat has two phases of systole and diastole [35]. The average resting heart rate in which the heart is pumping the lowest amount of blood for adults is between 60 bpm to 100 bpm. However, many factors such as the age, sex, fitness level and emotions can influence on the heart rate.

The heart has natural pacemaker consists of cells which generate electrical waves [36]. The heart rate is measured either manually by placing finger on the forearm or by using heart monitor devices such as an electric wrist, ECG.

The ECG is a graphical recording of the electrical activity through the heart. The first ECG was developed by the Dutch physiologist Willem Einthoven in the beginning of 20th century.

The Holter-monitor was developed after the invention of the ECG; it is a portable computerised 24-hour ECG monitoring systems [37].

The first HR monitor was developed in 1980. It consists of two components: a transmitter was attached around the chest and a wrist-worn receiver [38]. The portable heart rate monitors, which are widely used nowadays, are considered very easy to use, cheap, and reliable. The good thing of those devices, that the athletes can adjust the exercise intensity based on the recommended heart rate, as we will discuss later in this study, how using a portable device such as an accelerometer combined with smartphone will enable the exerciser to improve his cardiovascular fitness by investigating the parameters change during exercise and rest.

Another fact to consider when using those devices, that they are very reliable, and so many studies have been done to compare the results of those devices with the traditional ones, and the result were same.

Temperature is considered an external factor that effect on the heart rate, the heart rate in a high temperature environment will be higher than at low temperature environment of the same exercise intensity.

Heart rate is important to determine the exercise intensity. It is the quantity of energy required per minute to perform a specific activity (KJ/min), a study by [39] has classified the physical activity intensity based on heart rate reserve ($HR_{reserve}$) and maximum heart rate (HR_{max}) to express intensity. $HR_{reserve}$ is defined as the difference between the HR_{max} and the HR_{rest} is expressed by equation 2.2:

$$\mathrm{HR_{reserve}} = \mathrm{HR_{max}} - \mathrm{HR_{rest}} \qquad \text{Equation 2.2}$$

HR_{max} is the highest number of beats per minute (bpm) during maximum exertion. It is not dependent of cardiovascular fitness or physical condition, but may vary person to person and reduced with age due to properties of the heart [40].

The equation of Inbar [41] is considered to be the most accurate and widely used to calculate the maximum heart rate is given by equation 2.3:

$$\mathrm{HR_{max}} = 205.8 - 0.685 \text{ x (age)} \qquad \text{Equation 2.3}$$

HR_{rest} is the value of the HR while resting or not doing any exercise, the best time to find out the HR_{rest} is at wake up time. The lower the HR_{rest} is the more and great fitness health level. HR_{rest} can go as low as 30 bpm. One of the great athletes Miguel, in duration who is a five time winner of the Tour de France reported to have a resting heart rate of 28 bpm.

2.2.1.3 Electro-cardiogram

The electrical signals generated by cardiac muscle during depolarization and repolarization spread into the tissues around the heart and are conducted through the body fluids. A small part of this electrical activity reaches the body surface, where it can be detected using recording electrode placed on the skin. The recorded signal is called an electrocardiogram (ECG). It can provide useful information about the heart's status such as abnormal heart rates and any damage [30]. The three different parts of ECG are the P wave, the QRS complex and T wave (Figure 2.5).

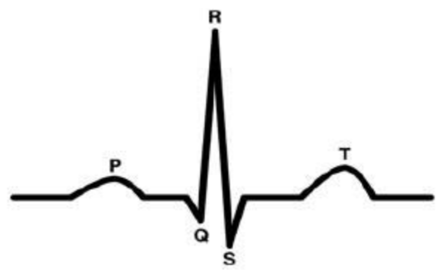


Figure 2.5: The ECG during normal heartbeat.

A normal ECG has three components: the P wave represents atrial depolarization, the QRS complex represents ventricular depolarization and the T wave represents ventricular repolarization.

2.2.2 Respiratory system

The process of respiration includes external respiration and internal respiration. External respiration, involves both bringing air into the lungs (inhalation) and releasing air to the atmosphere (exhalation) while cellular respiration, exchanged O_2 and CO_2 between the cells and blood vessels.

Respiratory system is consisting of specific organs that take oxygen from the air by inhaling and exhaling carbon dioxide [42]. The respiratory system is divided into two main parts. The upper part consists of nose, nasal cavity and the pharynx and the lower part consists of lungs, bronchi and the alveoli (Figure 2.6).

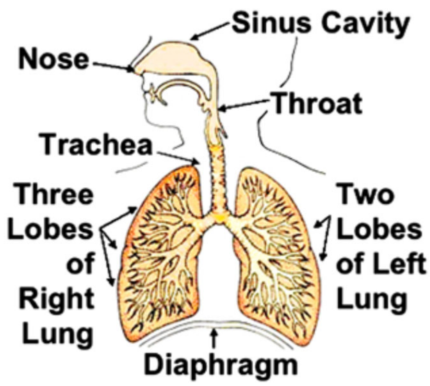


Figure 2.6: The Human Respiratory System. Adapted from [43].

The lungs are the main organs of the respiratory system; it takes oxygen from atmosphere and remove carbon dioxide from the body. Each lung is divided into sections, called lobes. The right lung has three lobes and the left lung has two lobes (Figure 2.6). It is further divide into smaller and smaller tubes, which is very tiny air sacs called alveoli. Inhaled air passes through alveoli where the O_2 pass through the alveolar walls into the blood and CO_2 pass through the capillary walls into the alveoli [43].

The diaphragm is an important structure of respiration located the bottom of the lungs. It controls breathing and separates the chest cavity from the abdominal cavity. When a breath is taken, it flattens and the lungs expand, inhaling air into the lungs. During exhalation, it relaxes, air flows out, allowing the lungs to deflate.

In a cellular respiration process use O_2 and produce CO_2 while deriving energy from nutrient molecules. The ratio of CO_2 produced to O_2 consumed is refers to respiratory quotient (RQ). It varies depending on the foodstuff consumed and is expressed by equation 2.4 [30]:

$$RQ = CO_2 \text{ produced} / O_2 \text{ consumed} \qquad \text{Equation 2.4}$$

When carbohydrate is used, the RQ is 1, it means for each molecule of O_2 consumed, one molecule of CO_2 is produced. The RQ for fat and protein is 0.7 and 0.8 respectively. A typical American diet consisting of a mixture of these three nutrients, average resting O_2 consumption is about 250 mL/min, and CO_2 production about 200 mL/min, the average RQ is 0.8.

2.2.2.1 Maximal oxygen consumption

VO_{2max} is the maximum rate of oxygen consumption measured during maximal exercise intensity, which cannot be increased despite further increase in workload, reflects the limits of the cardiorespiratory system [6]. Regular exercise improves health status by increasing cardiorespiratory fitness, which decreases cardiovascular disease, diabetes, cancer and problems associated with old age.

It considered the gold standard measure of aerobic fitness [44]. It means the maximum oxygen consumption (VO_{2max}) at which an individual's body can transport and utilize oxygen during high intensity of exercises. VO_{2max} is considered to be the best parameter of aerobic capacity, this variable measures the exercise capacity and reflecting the ability of the cardiorespiratory fitness of the individual. It is estimated by considering the transport capacity of O_2 to the tissues and use of it [45]. It is expressed either as an oxygen per minute (l/min) or per kilogram of bodyweight per minute (ml/kg/min).

The maximal rate at which an individual can use oxygen to produce energy, depends on many factors such as the size, the strength and rate of the lungs and their ability to air in, as well as the size of the heart, the blood volume and oxygen carrying capacity, the muscle size and its efficiency of extracting oxygen. Fitter people have a higher VO_{2max} than normal or untrained people, the average is around 5-40 ml/kg/min, but fit individuals can reach up to 90 ml/kg/min.

As we have discussed earlier, to perform exercise, which lasts more than three minutes, the oxygen must involve that yields more ATP that in turn produce more energy that enables athletes to carry out such exercise. The more amount of inhaled oxygen enables our body to perform better results in doing exercises.

VO_2 or maximal oxygen uptake is a key parameter used to measure cardiovascular fitness and efficiency. According to Fick equation, VO_2 is described as: at steady state, the uptake of oxygen is the product of arteriovenous oxygen difference and cardiac output [46] is expressed by equation 2.5 and 2.6:

$$VO_2 = \text{Cardiac Output } (Q) \times VO_2 \text{ Difference} \qquad \text{Equation 2.5}$$

Where:

$$\text{VO}_2 \text{ Difference} = CaO_2 - C\bar{v}O_2 \qquad \text{Equation 2.6}$$

Q: is the total volume of blood pumped by the heart per unit time.

CaO_2: is the oxygen content of arterial blood.

$C\bar{v}O_2$: is the oxygen content of mixed venous blood.

Several methods were developed for the determination of maximal oxygen uptake such as using treadmill running, bicycle ergometer and gas analyzer. Treadmill running methods involves to measure the oxygen concentration in the inhaled and exhaled air during graded exercise test within a laboratory. The other method is within free environment field and in this method there is no control on the movement of the exerciser where VO_{2max} is reached. At this stage oxygen consumption remains steady state after increase in the exercise intensity. At this point aerobic cannot consume any more oxygen for ATP production.

It was reported that that maximum oxygen uptake obtained by a cycle ergometer is lower than the VO_{2max} measured during treadmill running by 4-23%. It was also found that cyclists could achieve higher VO_{2max} values on the bicycle ergometer than on the treadmill. Other studies pointed out that VO_{2max} obtained using these methods are good agreement between them on a group basis but not so good on an individual basis [47]. Therefore, direct measurement of VO_{2max} using these methods were contradictory.

Oxygen consumption level can be measured using $K4b^2$ portable metabolic analyzer during exercise outside the laboratory in a natural environment. Although this method is accurate, problem is within the analyzer itself, because it is very expensive to have such equipment.

Measuring VO_{2max} can be dangerous when individuals are not considered healthy subjects, as any problems with the respiratory and cardiovascular systems will be greatly exacerbated in clinically ill patients. VO_{2max} measurements using traditional method is risky. Therefore, an indirect or predicted method of measuring VO_{2max} is useful. In this method depends on developing protocols to estimate the VO_{2max} from another variable such as heart rate. These are similar to a VO_{2max} measurements but they are not carried out till reaching the maximum of the respiratory and cardiovascular systems and are called sub-maximal tests [48]. Predicted VO_{2max} from submaximal performance HR is within 10-20% of the actual VO_{2max} [49]. However, this percentage may be beneficial for measuring individuals who have difficulties in finishing or performing maximal graded test such as elderly and pregnant women.

The linear relationship between heart rate and oxygen consumption is well documented. This relationship is used to estimate VO_2. Oxygen consumption increase with the increase in heart rate. During exercise, oxygen is increased distributed to the muscles that improve aerobic capacity and produce energy (ATP). Therefore, the estimation of energy can also be based on the relationship between HR and VO_2, however, the accuracy of predicting both energy and VO_2 has limitations because the relationship is curvilinear at very low and very high exercise intensities. The relationship between VO_{2max} and HR_{max} is shown in Table 2.1. In addition, the training zones, exercise intensity and their corresponding value for VO_{2max} is shown in Table 2.2 [50].

Table 2.1: Relationship between HR_{max} and VO_{2max}.

% VO_{2max}	**% HR_{max}**
< 40	< 60
41-55	60-70
56-70	71-80
> 70	> 80

Table 2.2: Exercise Intensity Levels that Coincide with VO_{2max}.

Category	**%VO_{2max}**
Fat Burning (Low)	< 50
Aerobic (Moderate or Vigorous)	~ 50-70
Anaerobic (Very Vigorous)	> 70

2.3 Exercise, diseases and rehabilitation engineering

2.3.1 Cardiovascular diseases

Cardiovascular disease shows a continuous increase due to diabetes, aging, high cholesterol, high blood pressure, psychological stress, smoking, emotional, social life and shortage of physical activity. Every year, approximately 17.9 million people die due to cardiovascular disease [51]. It is needed to reduce the number of deaths to help patients back to work and a normal life. The Australian Heart Foundation recommended that participation in the cardiac rehabilitation programs (CRPs) is effective to support heart disease and help to prevent further heart problems. It was observed that the participation of outpatient in CRPs reduced after hospital discharge because of the economic burden of attending and the time constraints regarding hospital visits [52], [53]. Therefore, cost-effective home based cardiac rehabilitation program is needed in practice.

Maximal aerobic power VO_{2max} is an indicator of cardiovascular diseases such as coronary heart disease patients. Therefore, cardiac rehabilitation programs with an exercise such as continuous aerobic exercise is effective to improve cardiovascular fitness [54]. Thus, during cardiac rehabilitation program, the exercise is to be appropriate i.e. exercise intensity is not high or not too less. The patient's exercise intensity can be estimated by measuring heart rate (HR). Home-based cardiac rehabilitation programs has shown to be effective specially those offered in community centres [55, 56]. In homebased training exercise program, HR testing equipment such as electrocardiography (ECG) may not be available and efficient exercise cannot be performed according to CRP guidelines [52]. However, more research is required to better understand the needs of patients so as to provide effective rehabilitation and to improve overall heath. In this study, we used smart phone with integrated accelerometer to measure HR and estimated VO_{2max} and developed model for cardiac rehabilitation. This is relatively inexpensive, easy to operate and can be used for home based exercise program.

2.3.1.1 Cardiac rehabilitation

Cardiac rehabilitation (CR) aims to support people who has some form of coronary heart diseases and to return to an active and fulfilling lifestyle, and facilitate secondary prevention of the disease [57, 58]. It includes a Phase 1 inpatient exercise program such as early mobilisation, education and optimisation of medical therapy. It support the patient's care from the cardiovascular event (e.g., a myocardial infarction that put them in the hospital) to the time of discharge from the hospital. The specific signs and symptoms indicates by the patient are used to determine whether the patient should be placed in an exercise program, and if so, when to terminate the exercise session [59]. Phase 2 rehabilitation, which begins on hospital discharge. This phase involves exercise program including disease education, psychosocial care, provides essential support, encouragement, motivation and management of risk factor to acquire long-term self-management solutions needed for patients. After discharge from hospital, a portable digital device is useful while continuing home-based exercise training programs.

Exercise program is now used to treat some form of coronary heart diseases. However, the coronary heart disease patients with VO_{2max} less than 20 ml $kg^{-1}min^{-1}$ (Tables 2.3 and 2.4), need light exercise to achieve their maximum heart rate which is equal to 70-85% of maximal HR.

Table 2.3: Typical maximum oxygen intake level (ml/kg/min) for men adopted from [60]

	Age (Years)					
Rating	65+	56-65	46-55	36-45	26-35	18-25
Excellent	> 37	> 41	> 45	> 51	> 56	> 60
Good	33-37	36-41	39-45	43-51	49-56	52-60
Above average	29-32	32-35	36-38	39-42	43-48	47-51
Average	26-28	30-31	32-35	35-38	40-42	42-46
Below average	22-25	26-29	29-31	31-34	35-39	37-41
Poor	20-21	22-25	25-28	26-30	30-34	30-36
Very poor	< 20	< 22	< 25	< 26	< 30	< 30

Table 2.4: Typical maximum oxygen intake level (ml/kg/min) for women adopted from [60]

	Age (Years)					
Rating	65+	56-65	46-55	36-45	26-35	18-25
Excellent	> 32	> 37	> 40	> 45	> 52	> 56
Good	28-32	32-37	34-40	38-45	45-52	47-56
Above average	25-27	28-31	31-33	34-37	39-44	42-46
Average	22-24	25-27	28-30	31-33	35-38	38-41
Below average	19-21	22-24	25-27	27-30	31-34	33-37
Poor	17-18	18-21	20-24	22-26	26-30	28-32
Very poor	< 17	< 18	< 20	< 22	< 26	< 28

2.3.1.2 Benefits of cardiac rehabilitation

As most cardiac patients have improved aerobic capacity and reduce cardiovascular risk factors as a result of an exercise-based rehabilitation [61]. It was reported that higher VO_{2max} values, higher work rates are achieved without ischemia [62, 63]. The exercise program improves lipid profile (lower total cholesterol and higher HDL cholesterol) [64], blood glucose control, insulin sensitivity [65, 66] and visceral adiposity [66]. Also it improves quality of life and $VO_{2\ max}$ and reduces stress [67].

However, a proposed exercise program that provided by general practitioner (GP) or cardiologist made as a prescription for their cardiac patients is only available in the medical system, until a reliable, portable, homebased device is developed, and that is our part of research.

2.3.2 Diabetes mellitus

Diabetes is a chronic disease resulting from insulin (a hormone that regulates blood glucose) disorders either when the body cannot effectively use the insulin it produces or when the pancreas does not produce enough insulin [68]. In 2017, there are 451 million people (age 18-99 years) are estimated to have diabetes [69]. If these trends continue, by 2045, the International Diabetes Federation (IDF) predicts about 629 million people will have diabetes (Figure 2.7).

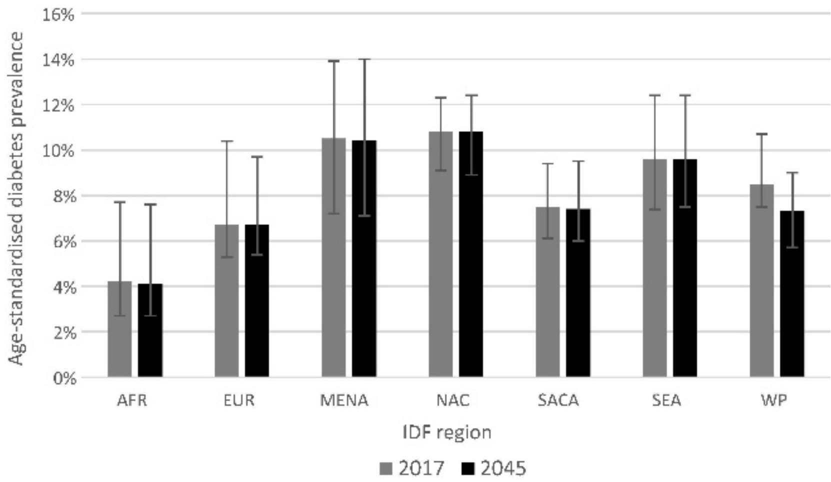


Figure 2.7: IDF predicts of diabetes 2017 – 2045. Adapted from [69]

People with diabetes lead to heart disease, kidney failure, stroke, and blindness [70]. Type 1 diabetes causes lack of insulin production in the body and Type 2 diabetes results resistance to insulin in the body.

Type 1 diabetes results from the destruction of insulin-producing pancreatic beta cells by a beta cell due to autoimmune pathologic process that occurs in the pancreas [71]. Insulin regulates the rate of blood glucose in the human body (Figure 2.8), the deficiency is controlled through regular insulin injections.

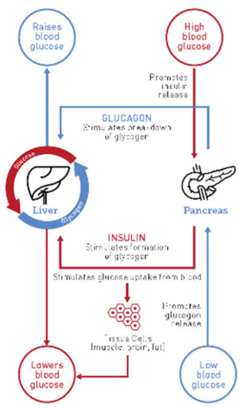


Figure 2.8: Insulin production and action Adapted [72].

Diet and insulin are the primary treatment of Type 1 diabetes to maintain blood glucose. An exercise program benefits for type 1 diabetes but most adults with type 1 diabetes participate less frequently in this program which may cause unhealthy lifestyles that contribute negative impact on metabolic control [73]. Therefore, the person must need to maintain a regular effective exercise schedule, as well as altering diet and insulin to achieved metabolic control.

Type 2 diabetes resistance to insulin sensitivity by the cells of the body. Overweight, obesity, age and lack of physical inactivity are mainly linked to type 2 diabetes [74, 75]. This disease is often managed by changing diet habits, regular exercise, lowering body fat and weight.

The guidelines recommend that patients with type 2 diabetes undertake 150 minutes per week moderate-intensity aerobic exercise, at 50% - 70% HRmax, at least 3 days per week with no more than 2 consecutive days without exercise [75] including strength training with light weights [76, 77].

It was reported that haemoglobin HbA1c and VO_{2max} values have been considered as an important indicators of blood glucose control in Type 2 diabetes [78]. They also pointed out that aerobic exercise reduces HbA1c, improves VO_{2max} and improves insulin sensitivity, which is important for the treatment of type 2 diabetes. Therefore, it is important for clear communication between the patients and the exercise supervisor (nurses or doctors in the hospital) while supervising and managing the overall exercise session by the supervisor. However, there are limitations because of individual's circumstances. In some cases, it is not possible for every diabetic individual to have their daily exercise activity in hospitals. By considering these issues, a reliable, portable, home-based device is proposed to help diabetes patients.

There are many devices are available to support physical activity that measure heart rate, intensity of movement, distance travelled as well as diabetes-specific devices including insulin pumps and blood glucose monitoring systems. This study uses wearable sensors, smartphone integrated with accelerator that are able to measure heart rate.

Study supports the benefits of physical activity and exercise in the prevention and treatment of type 2 diabetes [79]. However, lack of physical activity may result in the occurrence of a hypoglycaemic response [80]. The controlled diabetic has sufficient insulin such that glucose can be taken up into muscle during exercise and can catabolise stored glycogens in the normal increase from the liver due to the action of glycogenosis [81]. On the other hand, the diabetic with inadequate insulin experiences only a small increase in glucose utilization by muscle, but has the normal increase in glucose release from the liver. This leads to an elevation of the plasma glucose, resulting in hyperglycaemia [80]. In case of deconditioned individuals with Type 2 diabetes, duration of each exercise session must be carefully managed by someone (nurses or doctors), specially those are not physically active. Thus, there is need to develop new strategies or some smart devices and approaches to both prevent and treat the increasing prevalence Type 2 diabetes. The difference between Type 1 and Type 2 diabetics is shown in Table 2.5 [81, 82].

Table 2.5: Differences between Type 1 and Type 2 diabetes.

Characteristics	Type 1 (Insulin dependent)	Type 2 (Non-Insulin dependent)
Another name	Juvenile-onset	Adult-onset
Age at onset	< 20	> 40
Family history	Uncommon	Common
Development of disease	Rapid	Slow
Insulin required	Always	Common, but not always
Katoacidosis	Common	Rare
Body fatness	Normal/lean	Generally obese
Pancreatic insulin	None, or very little	Normal or higher

2.3.3 High blood pressure

If blood pressure left uncontrolled, it can lead to serious health problems. About 12.8% of deaths worldwide occur due to high blood pressure [84]. Approximately, 1 billion people worldwide have high blood pressure (BP) above the desirable range (Table 2.6). It is predicted that this number is expected to rise to 1.56 billion adults by the year 2025 [85]. Raised blood pressure is a major risk factor that causes about 51% of deaths from stroke and 45% from coronary heart diseases [86]. In 2014/15, around 6 million Australians (34%) aged 18 years and over had high blood pressure (systolic or diastolic blood pressure is ≥140/90 mmHg) above the recommendation level [87].

Blood pressure is positively correlated to coronary heart disease, heart failure, renal disease, kidney disease and visual impairment [84]. Therefore, dietary approaches and regular exercise is the first-line treatments to control high blood pressure, even when medicine is used [88].

Individual with elevated blood pressure between 120–139 mmHg (systolic blood pressure) and between 80–89 mmHg (diastolic blood pressure) is called prehypertension whereas hypertension is an elevation of systolic high blood pressure level of ≥140mmHg and/or diastolic high blood pressure level ≥ 90mmHg and [89, 90]

Prehypertension stage is not a medical condition; however, it is at more risk of developing hypertension [91] and is closely related with cardiovascular disease. Prehypertensive individuals should use exercise to control blood pressure.

Table 2.6: Blood pressure classification (mm Hg) [88]

Category	Systolic	Diastolic
Normal	< 120	< 80
High normal[a]	120-139	80-89
Mild	140-159	90-99
Moderate	160-179	100-109
Severe	≥ 180	≥ 110
Isolated systolic hypertension	≥ 140	≤ 90

[a] High-normal has been labelled as prehypertension

It was reported that a positive relationship between sedentary behaviour and the incidence of hypertension [92] that the National Heart Foundation [88], ACSM [94], US JNC on Detection, Evaluation and Treatment of High Blood Pressure [93], WHO and International Society of Hypertension [86] have all suggested regular physical activity is the first line treatment for patients with prehypertension. The guidelines also suggests exercise program for patients with hypertension grade 1: BP 140-159/80-90 mm Hg, or grade 2: BP 160-179/100-109 mm Hg (Table 2.6).

Physical exercise provide protective benefits for hypertensive individuals because it is a low cost intervention, reduces blood pressure and risk factors of other cardiovascular diseases if undertaken according to recommended guidelines. Physical activity greatly influenced blood pressure. Blood pressure is the force exerted by the blood against a blood vessel wall. During systole, where a stroke volume of blood enters the arteries from the ventricle, the maximum pressure exerted is systolic pressure (average 120 mm Hg). When blood is draining off onto the rest of the vessels, the minimum pressure is diastolic pressure (average 80 mm Hg) [30].

Physical exercise improves endothelial function, which produces paracrine signals. The endothelium is the single layer of cells that lines the entire cardiovascular system maintains blood fluidity, regulates vascular growth and vasomotor tone [95].

During physical activity, epithelial cells release other important paracrine signals which increases shear stress such as a frictional force exerted parallel to the blood vessels which produces nitric oxide in the endothelium [95]. Nitric oxide keeps the blood vessel healthy and enhances smooth muscle relaxation [96]. In addition, there are also vascular structural changes in response to blood flow such as diameter of existing arteries and veins, increasing length of the blood vessel and total cross sectional area including the growth of new blood vessels [94].

The low intensity of exercise prescribed at 40% to 70% VO_{2max} is effective in reducing blood pressure [94]. However, lower-intensity of exercise should be done regularly and for durations long enough to result in the expenditure of a large number of calories. It was reported that prescriptive elements such as exercise testing, patient category and monitoring, exercise intensity, type, duration and frequency to be included for each individuals (Table 2.7). They also pointed out that a variety of rhythmical and aerobic exercise is the preferred treatment strategy for all cardiovascular disease patients such as walking, running, cycling and swimming.

Table 2.7: Exercise prescription to patients with hypertension [95]

Category	A	B	C
	Grade 1: 1. Hypertensive <50 years 2. Pre-hypertensive with no suspected CVD <50 years	Grade 2: 1. Hypertensive without suspected CVD <50 years 2. Pre-hypertensive with suspected CVD 3. Pre-hypertensive >50 years	1. Hypertensive with suspected cardiovascular disease 2. Hypertensive with no suspected cardiovascular disease >50 years
Frequency per week	6-7 days	5-7 days	5-7 days
Exercise type	Aerobic activities	Walking, swimming, cycling until medically	Walking, swimming, cycling until medically evaluated
Exercise monitoring	Not necessary	Recommended	Recommended
Duration	At least 150 minutes per week.	Start with 20-30 minutes per day of continuous activity, then build to 30-60 mins per day	Start with 20-30 minutes per day of continuous activity, then build to 30-60 mins per day
Intensity of exercise	1. The first stage 20-30 minutes continuous aerobic activity for 3-4 weeks at comfortable pace (50-65%) of HR_{max} 2. After that exercise at up to 85% of HR_{max}	1. Light to moderate intensity until evaluated and conditioned. 2. After that maintenance aerobic program at up to 85% HR_{max}	1. Light to moderate lower intensity per day of continuous activity, can start initially with 20-30 minutes, 2. After that build to 45-60 minutes per day

2.4 Indoor and outdoor exercises

Exercising plays a vital role in improving and protecting the human being health; many diseases can be avoided by just exercising regularly, those diseases such as cardiovascular disease, cancer, blood pressure, diabetes and depression.

Regular exercise is protective against cardiovascular disease. Physically active people have higher levels of health-related fitness. Outdoors exercise results significantly greater effective. Because it is exposed to nature in combination with physical activity. The rate of intensity of individuals exercise showed greater speed and heart rate during outdoors exercise than during indoors exercise [97]. It was reported that individuals walk faster during self-paced walking exercise outdoors compared to indoors treadmill-based walking [98]. They also pointed out that indoors exercise is performed on static ergometers while outdoors exercise constitutes physical movement through an environment. It reflects environmental parameters may influence on physical activity.

Aerobic capacity is an indicator of various types of physical activities. The intensity, duration, type and mode of exercise are the important factors related to improve aerobic fitness [99, 100]. Physical activity increases the level of metabolic processes in the body involves the transformation of chemical energy into mechanical one [101]. VO_{2max} is used to describe the individual's aerobic fitness [102]. Oxygen uptake requirements of different tasks is shown in Table 2.8.

Table 2.8: Oxygen consumption requirements during different activities. Adapted from [103].

Activities, occupations and tasks	METs required	VO_2 (ml/kg/min) required
Sleeping	0.92	3
Inactivity (sitting quietly, watching TV etc.)	1.0	4
Car driving	2.0	7
Office work (computer)	1.6	6
Healthcare support (nursing)	2.8	10
Light housework (dishes)	2.1	7
Heavy housework (washing floors)	3.3	12
Walking 5km/h	3.2	11

Fishing	4.5	16
Gardening (digging)	4.4	15
Walking 7km/h	5.3	19
Walking upstairs	4.7	16
Backpacking 6.4km/h, 5% slope, 20kg	8.0	28
Cycling 20km/h	7.1	25
Cycling 30km/h	9.8	34
Running 9km/h	8.8	31
Firefighting	11.9	42
Ice hockey (competitive)	10.0	36
Running 22.5km/h	23.0	81
Running 19.3km/h	19.0	67
Running 15km/h	14.6	51

1 MET (metabolic equivalent) ≈ 3.5ml/kg/min

Most of the studies have estimated heart rate and oxygen uptake using hear rate monitor and portable gas analyzer during stair climbing. However, the objective of this study is to determine the heart rate in a cost-effective way. The aim of the study is to develop a nonparametric modelling that can accommodate the dynamic characteristics of the cardiovascular system based on the HR and VO_{2max} using accelerometer and heart rate (HR) in combination in a smartphone with software that allows downloading heart-rate data.

It is well known that HR has been taken as the variable to monitor exercise intensity during running and cycling [104]. It was also reported that HR shows a more stable variable during prolonged exercise (90 min) than other physiological variables [105]. Therefore, HR has been selected for this study during exercise.

Previous section we discussed, direct maximal oxygen uptake values measured using a cycle ergometer and during treadmill running are contradictory. This study designed commonly used indirect methods for the estimation of maximal oxygen uptake based on heart rate response to submaximal work.

2.4.1 Indoor exercises

Indoor exercises are improving aerobic fitness and controlling body weight. Studies was carried out to determine aerobic capacity using indoor exercise machines [106]. Two commonly used exercise machines are treadmill and bicycle ergometer.

2.4.1.1 Treadmill

The treadmill is a cardiovascular exercise machine and easy to use. It is useful for physical and clinical assessment for people and patients [107]. It was demonstrated that there is a strong relationship between HR and treadmill tests. The Vo_{2max} response of 12 college males was measured using treadmill protocol [108]. They found average VO_{2max} was 4.23 $Lmin^{-1}$. They concluded that the horizontal and inclined treadmill methods were produced approximately same VO_{2max}. They also reported that similar maximal oxygen uptake results using a horizontal treadmill and the step test procedures.

Most treadmills are not manually operated. Many of them complaints about the opportunity to rest and the position of the belt. Also at the end of treadmill exercise, in some cases reported nausea, breathlessness, chest pain and unsteady on their legs [109].

2.4.1.2 Bicycle ergometer

Bicycle ergometers are commonly used training devices to conduct performance based testing of cyclists to take measurements of physiological performance repeatedly under controlled conditions [110]. During steady-state cycling, blood flow increases with cardiac output and oxygen consumption [111]. Brain blood flow is also increases with the intensity of exercise. From low- to moderate-intensity exercise (cycling), blood flow increases while at higher exercise intensities, blood flow decreases [112].

The problem using the bicycle was saddle discomfort. The main complaints during exercise on the bicycle ergometer were pain in the muscle and shortness of breath [109].

2.4.2 Outdoor exercises

Outdoor exercise is associated with several affective benefits and motivation to participate in physical activities. Studies show that some physical benefits were associated with outdoor walking programs such as lower the risk of cardiovascular disease and obesity [113]. Two commonly used outdoor exercises are running and stair climbing.

2.4.2.1 Running

Running is a kind of aerobic activity has substantial health benefits. The World Health Organization has recommended at least 150 minutes of moderate-intensity or 75 minutes of vigorous-intensity aerobic activity each week, or a combination of both. It was found that running per day with speeds <6 mph reduced risks of cardiovascular disease [114]. It is documented that heart rate and VO_2 were linearly related with running speed [115].

2.4.2.2 Stair climbing

In the earlier section, we discussed cardiovascular disease risk factors related to aging, high blood pressure, diabetes, high cholesterol and shortage of physical activity. Traditional exercises are expensive and required specialised equipment. Therefore, cost-effective approaches are needed to increase physical activity to improve this risk and can be easily performed at home without assistance and expensive equipment. The stair climbing is a cost-effective alternative mode of exercise that is growing interests to public. The benefits of staircase climbing exercise are well documented to reduce type 2 diabetes and high blood pressure.

Stair climbing accelerates heart rate rapidly, and makes breathe faster to take in more oxygen. This improves VO_{2max} can utilize by the body during intense exercise [116]. As the heart rate increases, more blood is pumped within the body. In addition, tissue cells within the body take O_2 from the blood that oxygen oxidised nutrients for energy production [30].

It was reported that when young healthy adults climbed 11 stories consisting of 180 steps, the maximum heart rate and oxygen uptake were 90% and 80% during the last 30s of the ascent, which is corresponding to 9.6 metabolic equivalents (METs) of energy expenditure [17], is sufficient to improve cardiorespiratory fitness [117]. It was also reported that stepping exercises are intermediate between treadmill and bicycle exercise [109].

It was showed that 8 weeks of stair climbing produced a 17.1% increase in maximum oxygen uptake (VO_{2max}) and a 7.7% reduction of lipoprotein in young women [118]. Lipoprotein particle in the blood was responsible for depositing cholesterol in the body. They also pointed out that stair climbing is important to improve cardiovascular risk factors for sedentary young women. Other studies found that the stair-climbing increased quadriceps strength, maximal oxygen uptake and plantar flexion moments in young and middle-aged adults [119. 120]. Therefore, to prevent cardiorespiratory risk factors stairclimbing exercise may be incorporated in a daily routine for aerobic fitness improvements in seniors.

The main complaints were boring and a few of them found difficulty in maintaining a rapid rhythm, the steps looked slippery and weakness or pain in the leg muscles.

2.5 Interval training

Interval training involves alternating periods of hard exercise with periods of either relative or complete rest and refers to high-intensity interval training [121]. It needs to increase and decrease the workout intensity between exercise sessions and recovery periods [121]. Several studies have demonstrated that high-intensity interval training improve VO_{2max}, cardiovascular health, endothelial function, muscle oxidative capacity, and resting muscle glycogen [122, 123]. Also, it is significantly associated with weight loss, rehabilitation, general fitness, and the reduction of heart and pulmonary diseases [122]. In interval training protocol the athletes are able to maintain higher workload for longer period and hence achieve better results compared to the continuous exercise.

In earlier section, we discussed that The World Health Organization has recommended 150 minutes of moderate-intensity exercise or 75 minutes of vigorous-intensity exercise each week to prevent chronic disease. Tabata interval training initially developed by Dr. Izumi Tabata at the National Institute of Fitness and Sports in Tokyo. It was showed an increase in VO_{2max} (14%) along with 28% anaerobic capacity in Tabata method when taking short rest intervals between high intensity exercises [123]. Four commonly used training protocols are shown in Table 2.9.

Table 2.9: Popular high-intensity interval training protocols (Adapted from [121]

Name	Work interval and intensity	Rest interval and intensity	Series	Modality	Total time
Tabata	20 seconds at 170% VO_{2max}	10 seconds of rest or very low intensity	Repeat 8 times	Cycle ergometer, treadmill, body weight, track or resistance exercises	4 minutes
Wingate	30 seconds all out against constant force	4 minutes of active recovery low intensity	Repeat 4-6 times	Mechanically braked cycle ergometer (i.e., Monark)	18-27 minutes
Conventional	60 seconds at >90% HRR	60 seconds of rest or active recovery	Repeat 10 times	Cycle ergometer, treadmill, body weight, track or resistance exercises	20 minutes
Clinical	4 minutes at 85%-95% MHR	3 minutes of recovery at 60%-70% MHR	Repeat 4 times	Cycle ergometer, arm ergometer or treadmill equipped with handrails	25 minutes

2.6 Conclusion

In summary, regular aerobic exercise increases VO_{2max} and reduces the risk of cardiovascular disease. VO_{2max} is one of the most fundamental measures of human's aerobic fitness. There is a linear relationship between VO_2 and running speed/stepping. Mobile phone technologies are potentially enabling tools for the measurements of running speed/stepping along with heart rate. The concept and definition of these variables are presented in this chapter. The relationship between these two indicators has been used to predict maximal oxygen consumption. VO_{2max} can be measured either directly in a laboratory or indirectly with controlled protocols.

In this chapter, the relationship between exercise and energy systems is also outlined. In particular, the metabolic energy process under exercise conditions is clearly explained. It would be beneficial for a deep understanding of the intensity of exercise. It has been suggested that high intensity training program may be incorporated in cardiac rehabilitation programs for all cardiac patients. It has been reported that exercise and relevant biomedical devices can be useful to monitor cardiorespiratory diseases, such as cardiac diseases, diabetes, and high blood pressure. The details of diseases and exercise prescriptions are explained in this chapter.

Chapter 3 : Equipment and Tools

3.1 Overview

This chapter presents the equipment and tools used throughout this research work. Equipment such as COSMED $K4b^2$ was used to measure, collect and record volunteers physiological parameters such as VO_2 and VCO_2.

The measurement of oxygen uptake during sport or a real-life activities is of great interest for the development of training programs and the study of their effects on elite athletes or for assessing the efficacy of rehabilitation therapy.

The heart rate sensor that was attached to the participant’s chest connects to the smart mobile through BLE technology to measure the participant’s heart rate while exercising and to instruct the subject to respond based on their HR zone profiles.

In this study, we have implemented the training and rehabilitation control system on a smart mobile device and eZ430-Chronos watch. The smartphone is very popular nowadays and it is used by many people, however, due to the complexity of smart phones and the difficulty to use them by elderly people or patients, the control system is implemented on a small watch that is very cheap and easy to use.

Many programming languages used in this study to develop the training and rehabilitation control system such as C++ and SWIFT as we will explain later in this chapter.

The collected data exported to a desktop computer through Bluetooth and serial connection for further analysis and modelling.

3.2 Cosmed K4b^2

K4b^2 is a wearable electrical medical device designed to perform pulmonary function tests [124]. This portable gas analyzer device employs a breath-by-breath technology to measure and collect participants' physiological parameters such as ventilator, VO_2 and VCO_2 in lab or in the field using several sensors such as flow meter, oxygen sensor and carbon dioxide sensor. The subject can wear it during activity either in indoor or outdoor environment and it is capable of delivering real-time measurements in to a computer with saving data simultaneous.

The Cosmed K4b^2 gas analyzer, see figure 3.1 has been reported to be valid, accurate and reliable [125, 126]. Because of its convenience, it is accepted in many applications such as sports medicine research in human performance, occupational health, cardiology, cardiac rehabilitation, clinical nutrition.

Figure 3.1: K4b^2 portable unit

The Cosmed $K4b^2$ device consists of the following parts:

1. **$K4b^2$ portable unit.**

   The portable unit is powered by a rechargeable battery attached to the backside of a harness, contains the O_2 and CO_2 analyzers, sampling pump, UHF transmitter, barometric sensors and electronics. . The $K4b^2$ PU has a small display screen that shows in real time the following parameters: VT, VE, VO_2, VCO_2, R, HR, RF Marker, battery charge level, temperature and barometric pressure. The collected data is stored locally on the device as well as can be transmitted to a desktop computer for live monitoring.

   The portable unit allows the following functions:

   1. Patient data input.
   2. Environment data input (humidity).
   3. Gas and turbine calibration (automatic).
   4. Memory functions.
   5. Tests data management.
   6. Data loading to a PC (via RS232).

2. **$K4b^2$ receiver unit:**

   The Receiver Unit (RU) allows live data transmission to a desktop computer through RS-232 serial cable. The PU has a miniaturized transmitter module that has a transmission range of up to 800 meters is responsible to achieve the data transmission to the receiver unit.

3. **Battery charger:**

The Charging Unit (CU) allows the simultaneously charge of up to three Ni-Cd batteries and to supply the PU during the warm up time.

4. **Flowmeter:**

The system uses a bi-directional digital turbine. It opposes a very low resistance to flow (< 0,7 cmH2O/l/s to 12 l/s). The air passing through the helical conveyors, takes a spiral motion, which causes the rotation of the turbine rotor. The rolling blade interrupts the infrared light beamed by the three diodes of the optoelectronic reader. Every interruption represents 1/6 turn of the rotor, this allows to measure the number of turn in the time [124].

5. **Gas analyzer:**

The O_2 and CO_2 analyzers are temperature-controlled and the internal pressure and expired flow are monitored for an higher reliability if the measurements. The K4 b^2 uses Nafion Premature that is a semipermeable capillary tube capable of removing the humidity in excess without altering the gas concentrations. The analyzers calibration is automatic and shows both graphically and numerically the flow and concentration signals and the accuracy of the baseline/gain.

6. **External sensors:**

The device is equipped with many other sensors such as temperature, humidity and GPS.

Based on the recommendations from the $K4b^2$ manual, The $K4b^2$ device needs to be warm up and calibrated before any experiment as recommended by the manufacturer. The following steps explain the steps that we have taken before performing any experiment.

1. **Charging the batteries.**
   The charging unit allows charging of up to three batteries simultaneously. The green LED on the front panel indicates that the batteries are charging and the blinking LED indicates that the battery is fully charged. While in the field, the PU produces different types of beeps to warn user of the battery level, two beeps indicates half charged battery while three beeps indicates warns the user of the battery level, where two beeps indicates discharged battery. Figure 3.2 shows the charging unit connected to K4b^2 and charging three batteries at same time.

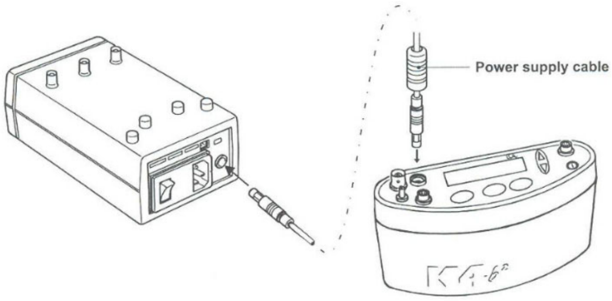


Figure 3.2: K4b^2 device connected to CU

2. **Warm up:**
   Before performing any tasks using the K4b^2 device, the unit must be connected to the charging unit. The charging unit allows charging the three batteries while warming up the device. The device must warm up for at least 45 minutes; however, the recommended warm up time is 60 minutes.

3. **Calibration:**
   Once the K4b^2 has warmed up as per the manufacturer recommendation, the sensors will need to be calibrated and the calibration process needs to be performed every time before carrying on any exercise to get the most optimal and accurate sensors values. Either calibration can be performed through the

desktop software or directly using the portable unit, however, it is recommended to calibrate the device using the desktop application. There are four types of analyzer calibration that needs to be performed on sequences as explained in the following section:

- Room Air Calibration:
  The room air calibration is the first calibration to be performed before any experiment, we connect the $K4b^2$ unit to the desktop computer using serial RS-232 cable, the sampling line must be disconnected from the unit and then using the software, we can run the calibration program to start the room air calibration as shown in figure 3.3. It is important to mention that all the values must be in black, otherwise, red values indicates some problem and the calibration process needs to run again.

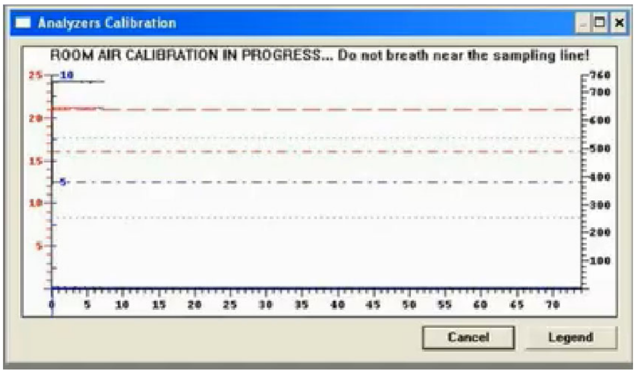


Figure 3.3: Calibration – Room air

- Reference Gas Calibration:
  In reference gas calibration, we connect the $K4b^2$ device to the gas cylinder as shown in figure 3.4. The recommended gas concentration is to use 5% of CO_2, 16% of O_2 and N_2 for balance. The calibration process starts by opening the cylinder valve and the pressure must be in the range of 44 to

73 psi and then by running the calibration program. The sampling line must be removed before starting the calibration.

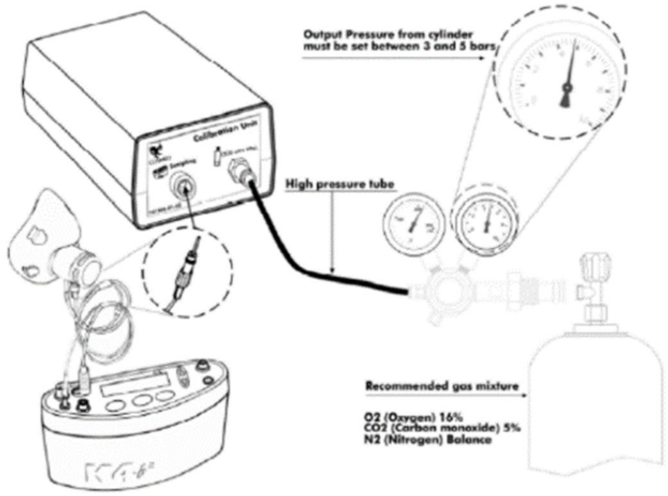


Figure 3.4: Calibration – Reference Gas

- Gas Delay Calibration:
  The participant needs to wear the mask to perform the Gas Delay calibration. Initially the sampling line is removed and then the air calibration takes place and then a message indicates the sampling line needs to be connected to the flowmeter, and the user needs to breath into the mask in time with beeps that begin to inhale and exhale until the message pop ups indicting the calibration is done.

- Turbine Calibration:
  The Turbine calibration is the last calibration to be performed and using the desktop application, we can perform this calibration.

The K4b^2 is a versatile system. It can be used for indoor or outdoor exercises without any limitations. Test can be carried out in the following three different configurations:

1. **Holter Data Recorder**:

   This is the most common mode for outdoor exercises where the system can be used without the receiver unit and the data is stored in internal memory of the portable unit that can store up to 16 thousands of breath. The data can be then transferred to the computer through RS 232 serial port. In this study, we have carried all the tests using this configuration.

2. **Telemetry Data Transmission:**

   To allow the researcher to monitor the participant online, the PU has the ability to transmit the data to the receiver unit that is connected to a PC by serial port, however the data is also stored locally to prevent any data loss.

3. **Serial Station:**

   The serial station gives the researcher the option to perform the tests in the laboratory and in this mode; the PU is connected to the PC using RS232 serial port.

The last step to do before performing any experiment is enter the participants data such as age, sex, height and weight as shown in figure 3.5:

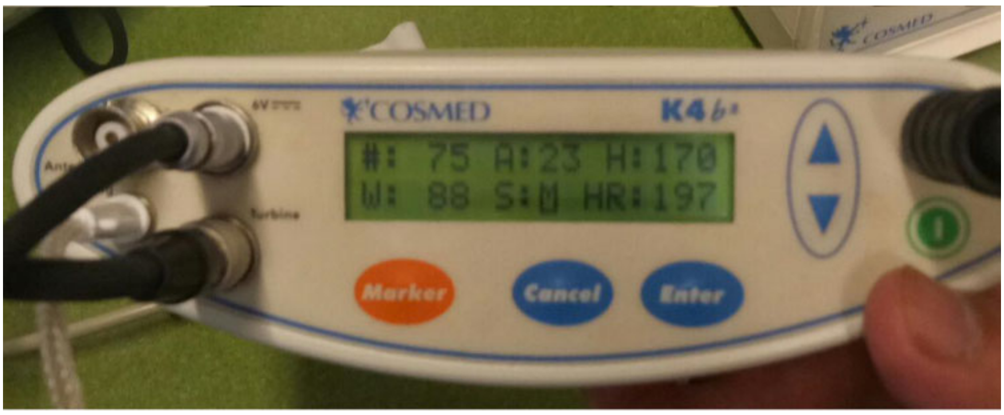


Figure 3.5: $K4b^2$ – Entering Participants data

3.3 Smartphone

Nowadays, smart mobiles play a very important role in our daily routine life, and the latest smart mobiles such as Apple iPhone 6s Plus [127] is equipped with many integrated sensors that make it an excellent choice as a training and rehabilitation device.

The Apple iPhone 6s Plus smartphone is equipped with many sensors such as accelerometer, gyroscope and barometer which are very important in implementing health control system. The health control system was developed using SWIFT programming language and deployed in Apple iPhone 6s Plus. In this section, we will explain in details the Apple iPhones' built in sensors that we have used in this study.

3.3.1 Accelerometers

The accelerometer is a very tiny device that is nowadays integrated with many devices such as mobiles and watches are basically an electromechanical device that measures acceleration forces either static forces such as gravity or dynamic forces such as movement. The acceleration is measured in meters per second (m/s^2) or in standard gravity (g), which equals to 9.8 m /s2 and the accelerometer can measure this acceleration in one, two or three axes. Figure 3.7 shows the iPhone 6s Plus accelerometer 3-axes.

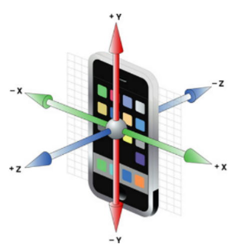


Figure 3.6: iPhone - Accelerometer 3-axes

The Apple iPhone 6s Plus contains a six-axis InvenSense IMU device that contains 6-axes gyroscope and 6-axis accelerometer, and a Bosch BMA280 three-axis accelerometer.

The InvenSense MPU-6500 is 6-axis motion tracking device for smartphones, tablets, and wearable sensors. It integrates a 3-axes accelerometer, a 3-axis gyroscope and on-board Digital motion Processor in a small, 3 mm x 3 mm x 0.9 mm QFN package as shown in figure 3.8 [128], while the Bosch BMA280 is an advanced, ultra-small, tri-axial, low-g acceleration sensor with digital interfaces, aiming for low-power consumer electronics applications [129].

The benefit of having two accelerometers in iPhone 6s Plus is to give the developers the option to choose between high sensitivity accelerometer such as InvenSense and the lower power consumption such as the Bosch BMA280 accelerometer.

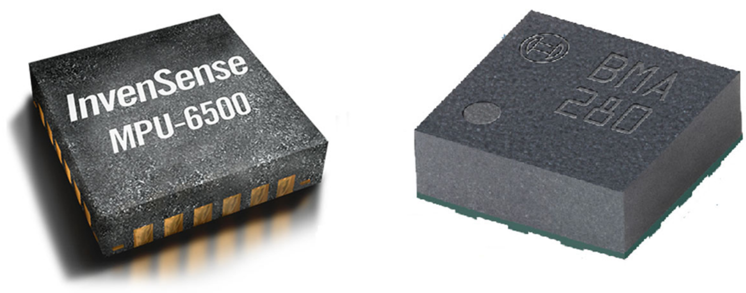


Figure 3.7: InvenSense 6500 & BMA280 accelerometer

The technical specifications of both the InvenSense MPU-6500 [128] and the Bosch BMA280 [129] is shown in table 3.1:

Table 3.1: Accelerometers Technical Specifications

Parameter	InvenSense MPU-6500	Bosch BMA280	Units
Acceleration scale range	±2, ±4, ±8, ±16	±2, ±4, ±8, ±16	g
ADC word length	16	14	bits
Sensitivity Scale Factor	16,384	4096	LSB/g
Operating Temperature	-40 - +85°	-40 - +85°	°C
Cross axes Sensitivity	2	1	%
Output data rate	4000	2000	Hz
Cold start up time	30	3	ms

3.3.2 Gyroscope

Gyroscope is a device consisting of a wheel or disc mounted so that it can spin rapidly about an axis that is itself free to alter in direction. The orientation of the axis is not affected by tilting of the mounting, so gyroscopes can be used to provide stability or maintain a reference direction in navigation systems, automatic pilots, and stabilizers [130]. Gyroscopes measure the rate of rotation of an object around a specific axis, either 1-axis, 2-axis or 3-axis. Figure 3.9 shows the iPhone 6s Plus accelerometer 3-axes.

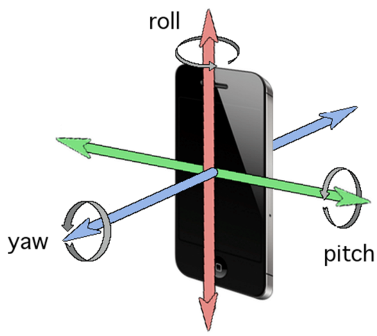


Figure 3.8: iPhone - Gyroscope 3-axes

The Apple iPhone 6s Plus is equipped with a 3-axes gyroscope from InvenSense that is integrated with 6-axis accelerometer as an IMU device. The InvenSense MPU-6500 gyroscope parameters [128] are shown in Table 3.3:

Table 3.2: Gyroscope Technical Specifications

Parameter	InvenSense MPU-6500	Units
Gyroscope scale range	±250, ±500, ±1000, ±2000	°/s
ADC word length	16	bits
Sensitivity Scale Factor	131	LSB/(°/s)
Operating Temperature	-40 to +85	°C
Cross axes Sensitivity	±2	%
Output data rate	8000	Hz
Cold start up time	35	ms

3.3.3 Barometer

Barometer is a device that used to measure the air pressure, The Apple iPhone 6s Plus smartphone is equipped with a barometer that can determine the altitude. Based on the altitude value reading, the smart phone application can track our vertical movement without the need of GPS assistance. In this study, we have utilised the barometer to determine whether the participants are ascending or descending the staircase.

3.4 eZ430-Chronos Watch

The eZ430-Chronos watch developed by Texas Instruments (TI) is a very powerful development system based on TI CC430 development system that can be used by elderly people or during cardiac rehab – outpatient phase to control and monitor the exercise intensity in order to increase and strengthening the cardiovascular fitness system.

Based on the CC430F6137, the eZ430-Chronos is a complete CC430-based development system, featuring a 96-segment LCD display and provides an integrated pressure sensor and 3-axis accelerometer for motion sensitive control. The integrated wireless interface allows the eZ430-Chronos to act as a central hub for nearby wireless sensors such as pedometers and heart rate monitors. The eZ430-chronos watch may be disassembled to be reprogrammed with a custom application and includes an eZ430 USB programming interface [131].

Figure 3.9: eZ430-Chronos Watch

The main features of the eZ430-Chronos are [131]:

- Fully functional sports watch based on the CC430F613, MSP430 with integrated sub-1-GHz wireless transceiver.
- Watch can be reprogrammed for custom wireless applications.

- Highly integrated watch includes on-board three-axis accelerometer, pressure sensor, temperature sensor and voltage sensor.
- 96-segment LCD display driven directly by CC430.
- Can be paired wirelessly with heart rate monitors, pedometers, or other devices based on RF transceivers such as the CC430 or CC11xx series.
- Includes an eZ430-RF USB emulator that connects the eZ430-Chronos to a PC for real-time in-system programming and debugging.

The Code Composer Studio (CCS) [131] software is a very powerful programming and microcontroller development tool developed by Texas Instruments was built on eclipse environment has been used in this study to program and customize the eZ430-Chronos watch that is based on the MSP430 microcontroller family from TI.

3.5 Heart Rate Sensors

In this study we have used two heart rate sensors to measure heart rate while exercising, The polar H7 Bluetooth Smart Heart Rate Sensor is paired with the iPhone while the BM-CS5 chest strap from BM innovation was paired with the eZ430-Chronos watch to control the exercise intensity and guide the participant during the exercise.

3.5.1 Polar H7 Heart Rate Sensor

Polar H7 Bluetooth Smart Heart Rate Sensor [132] is a very powerful HR belt that features BLE technology, strong battery life and water-resistant used in this study. The Polar HR belt connects to the developed application through BLE (Bluetooth Low

Energy) technology to track the athletes' performance and improve their cardiovascular fitness through continuous monitoring.

Figure 3.10: Polar HR Sensor

3.5.2 BM-CS5 Chest Strap

The BM-CS5 chest strap from BM innovation [133] has been used in this study to measure the heart rate while exercising and send them back to eZ430-Chronos watch using ultra-low power BlueRobin data transmission technology.

Each chest strap has a unique ID assigned that can be used to identify the user and pair the chest strap to a receiver. Built-in data collision prevention allows the chest strap to be used in multi-user environments, where a large number of chest straps transmit their data to a single receiver.

There are two models of this chest strap:

1- BM-CS5 868/915 MHz with up to 400m range.

2- BM-CS5 868/915 MHz with up to 10m range.

Figure 3.11: BMi Chest Strap

3.6 Development Tools

Many programming languages were used in this study to develop applications from the scratch or to customize the firmware in order to fulfil the requirements of the proposed physiological control systems. The SWIFT programming language from Apple used to develop iPhone application, C++ programming language was also used to reengineer the eZ430-Chronos watch while the K4b^2 device software from COSMED were used to calibrate the sensors and download the recorded data. In this section, we will explain in details the programming languages used in this study.

3.6.1 Code Composer Studio and C++

The CCS software is a very powerful programming tool from Texas Instruments that is built on eclipse architecture has been used in this study to reengineer the eZ430-Chronos watch that is based on the MSP430 microcontroller family from TI.

Code Composer Studio as shown in figure 3.13 is an integrated development environment (IDE) that supports TI's Microcontroller and Embedded Processors portfolio. Code Composer Studio comprises a suite of tools used to develop and debug embedded applications. It includes an optimizing C/C++ compiler, source code editor, project build environment, debugger, profiler, and many other features. The intuitive IDE provides a single user interface taking you through each step of the application development flow.

Familiar tools and interfaces allow users to get started faster than ever before. Code Composer Studio combines the advantages of the Eclipse software framework with advanced embedded debug capabilities from TI resulting in a compelling feature-rich development environment for embedded developers [131].

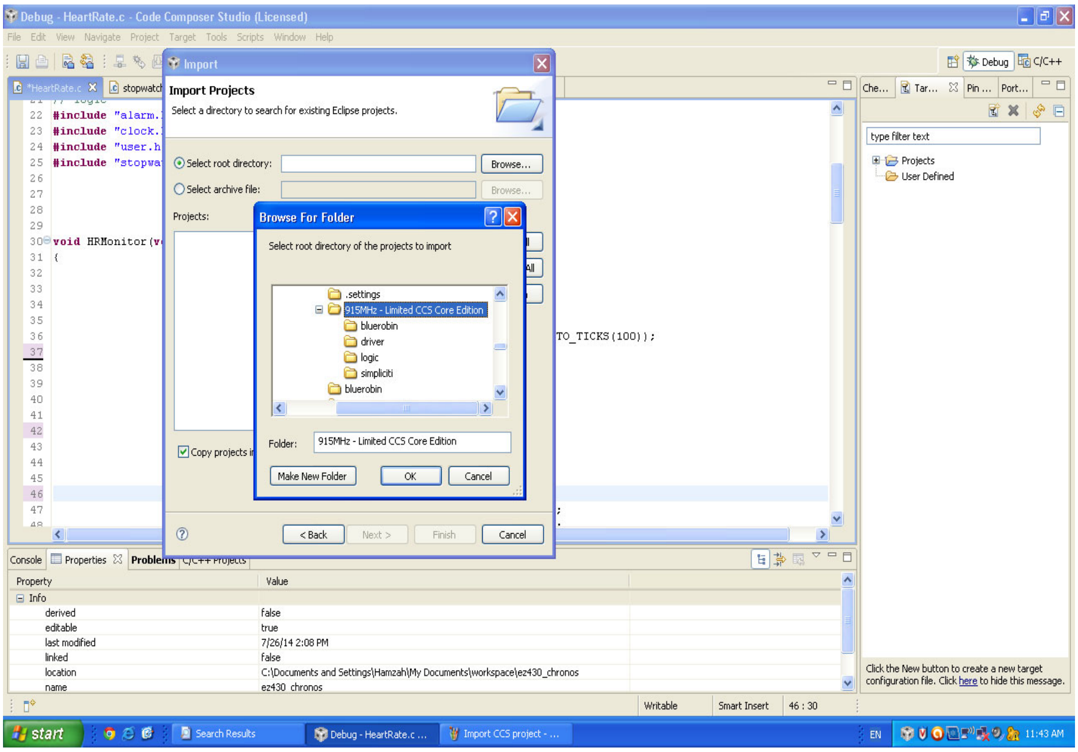


Figure 3.12: CCS

C++ is a high-level programming language, which is an extension of C language and has been developed by Bjarne Stroustrupis. C++ is a very powerful general-purpose object oriented programming (OOP) language; C++ is an excellent option for microcontrollers programming.

C++ is a general-purpose object oriented programming language. It is considered to be an intermediate level language, as it encapsulates both high and low level language features. Initially, the language was called 'C with classes' as it had all properties of C language with an additional concept of 'classes'. However, it was renamed to C++ in 1983.

C++ is one of the most popular languages primarily utilized with system/application software, drivers, client-server applications and embedded firmware.

The main highlight of C++ is a collection of pre-defined classes, which are data types that can be instantiated multiple times. The language also facilitates declaration of user defined classes. Classes can further accommodate member functions to implement specific functionality. Multiple objects of a particular class can be defined to implement the functions within the class. Objects can be defined as instances created at run time. These classes can also be inherited by other new classes which take in the public and protected functionalities by default.

C++ includes several operators such as comparison, arithmetic, bit manipulation, logical operators etc. One of the most attractive features of C++ is that it enables the overloading of certain operators such as addition.

C++ is an Object Oriented Programming language, the OOP is defined as a programming paradigm that represents the concepts of "objects" that have data fields (attributes that describe the object) and associated procedures know as methods. Objects, which are usually instances of classes, are used to interact with one another to design applications and computer programs [134].

3.6.2 Xcode and SWIFT

Xcode is an Integrated Development Environment (IDE) application developed by Apple [135] to create applications for Mac, iPhone, iPad, Apple TV and Apple Watch. The first version of Xcode was released in 2003 and can be downloaded through Apple store free of charge.

Xcode has many features that enables developers to create amazing application form all Apple platform. Figure 3.13 shows the Xcode interface. The source code editor enables developer to transform or refactor code more easily, see source control changes alongside the related line, and quickly get details on upstream code differences. Developer can build instrument with custom visualization and data analysis. Swift compiles software more quickly, deliver faster apps, and generates even smaller binaries [135].

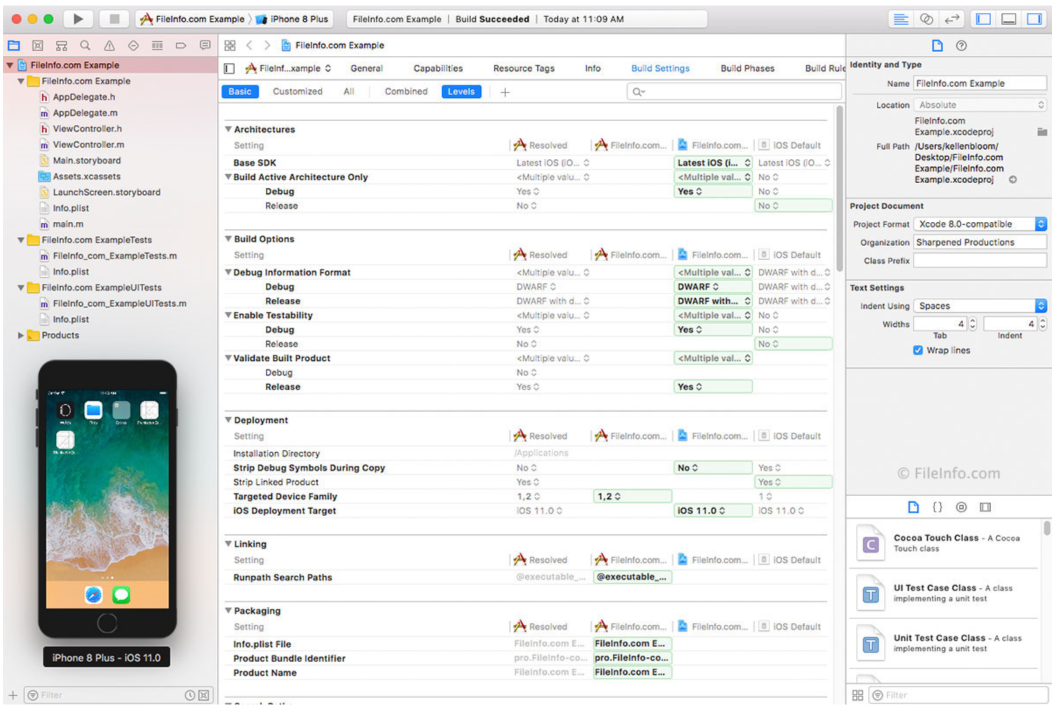


Figure 3.13: Xcode Interface

The main features of Xcode can be summarized as following:

1. Assistant editor
2. Version editor
3. OpenGL frame capture
4. Integrated build system
5. Simulator
6. Compilers
7. Graphical debugger
8. Static analysis

SWIFT is a powerful and intuitive programming language developed by Apple for macOS, iOS, watchOS, tvOS and Linux applications [136]. SWIFT introduced at Apple's Worldwide Developers Conference in 2014 and became one of the fastest growing programming language with high demand for SWIFT developers.

The training and rehabilitation control system for smart phones was developed using SWIFT programming language. The main features of SWIFT programming language is explained as following:

- **Open Source:**
  Apple decided to make the Swift technology an open source for all in 2015 [136] in order to make a defining language, which results in more community members working actively to add more feature and extend the support to more platforms such as Android.

- **Safety:**
  Swift eliminates entire classes of unsafe code [136], variables must be initialized before use, also, the objects can never be nil. The compiler does not allow developer to use a nil object; this act makes the code cleaner and safer and prevents runtime error in the developed application.

- **Package manager:**

  Swift Package Manager is a cross-platform tool for building Swift libraries and executables, making it easy to create and manage dependencies [136].

- **Fast:**

  Swift was built to be fast. Using LLVM compiler, Swift code is transformed into optimized native code that gets the most of modern hardware [136]. Building applications with SWIFT is easier and is faster. Swift is 2.6x faster than Objective-C and 8.4x faster than Python [137].

- **Automatic Memory Management:**

  Swift uses Automatic Memory Counting (ARC) technology that works on developer behalf to determine which class instances are no longer in use and delete them which results in increasing the developed applications performance.
- **Decrease Memory Footprint:**

  Using third party code such as framework or libraries in the developed application is common in the development cycle; however, Apple introduced the idea of using dynamic libraries that can be used by many applications without locking them in each application, which in turn decreases the application size.

Swift defines away large classes of common programming errors by adopting modern programming patterns [138]:

- Variables are always initialized before use.
- Array indices are checked for out-of-bounds errors.
- Integers are checked for overflow.
- Optionals ensure that nil values are handled explicitly.
- Memory is managed automatically.
- Error handling allows controlled recovery from unexpected failures.

3.6.3 COSMED K4b^2 Software:

The COSMED K4b^2 device is equipped with a PC software that can be used for monitoring and recording the experiments. The software consists of two programs, a spirometry and ergometry. In this research, we have used the ergometry program that is specialized in the Cardiopulmonary Exercise Testing (CPET).

Using this application, the system can be calibrated before performing any experiment also, this application allows us to download and manipulate the recorded data. Figure 3.14 shows participant VO_2 data while exercising.

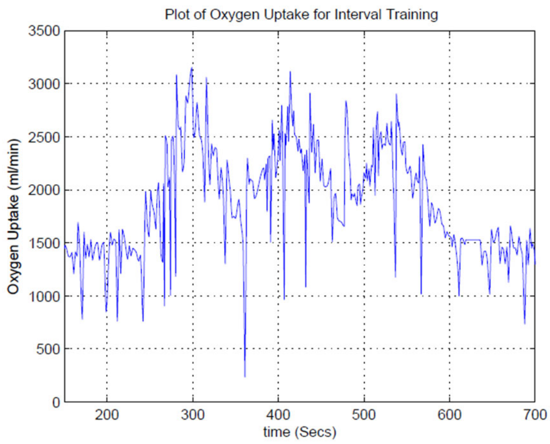


Figure 3.14: Participants'' VO_2 representation in COSMED Software

3.7 Conclusion

In this chapter, we have explored the equipment and tools used in this study to develop the training and rehab control system. The Cosmed K4b^2 device used in this study to measure the participant's physiological parameters. The control system was implemented on a smart mobile device and eZ430-Chronos watch. The smart mobile application utilizes built-in sensors to control the intensity of the exercise. An eZ430-Chronos watch is a good option for elderly people or for cardiac rehab patients. The control system was developed using many programming languages such as C++ and SWIFT.

Chapter 4 : Training and Rehabilitation Control System Design

4.1 Introduction

In this study, we have implemented our training and rehabilitation control system in two different environments. The first environment is for smartphone users, while the second one was built for users who cannot get access to a smartphone either because they are expensive or difficult to use by the elderly and patients.

The Apple iPhone is a very popular smartphone and has many embedded sensors that make it ideal for athletes' or for people who are willing to increase and strength their cardiovascular fitness health.

The eZ430-Chronos watch from Texas Instruments is very cheap and easy to use watch with many embedded sensors that make it an ideal option for an outpatient rehabilitation program.

In this chapter, we will explain in details the developed control system that we have built and implement on the smartphone and eZ430-Chronos watch.

4.2 Smartphone Control System

The Apple iPhone 6s Plus is equipped with many sensors such accelerometers, gyroscope, barometer that has been utilized to build an effective control system.

There are two accelerometers built in the Apple iPhone 6s Plus which enabled us to detect the number of steps in real time. The accelerometers frequency is very high, however for the purpose of this study; we set the accelerometer frequency to 10 Hz.

The developed control system utilizes the built in accelerometers to detect the number of steps while ascending or descending the stairs and the barometer to detect whether the participant is ascending or descending the staircase. In addition, the gyroscope helps the participant to determine the walking direction.

The accelerometer and gyroscope are extremely sensitive and this result in a noisy signal, which must be first, filtered and smoothed using digital filters. In this study, we have applied the low pass filter to the accelerometer and gyroscope raw data to get better signal. The accuracy of the developed algorithm is very high as we will explain later in this chapter.

The developed smart mobile application guides the user throughout the exercise duration that lasts for 720 seconds using voice commands. The user is required to respond immediately to the voice commands that activate whenever the user reaches his on set or off set exercise. The exercise duration can be adjusted based on the user requirements.

The system counts every step whether ascending or descending the staircase; also, it maintains the walking pace and alert the user whenever he is walking fast. The system also watch the user direction and warn him whenever he is not facing forward to avoid any injury during the exercise. The heart rate is monitored beat by beat through the Polar heart rate monitor that is connected to the smart mobile using BLE technology.

Data such as accelerometers x, y, z data, HR, Steps, Pace, and Time recorded by the smart phone application using the Apple Core Data technology and then exported to a desktop computer through Bluetooth Low Energy connection for further analysis and modelling.

4.2.1 Steps Detection

Combining raw data from both accelerometer and gyroscope gives us a valuable information during the exercise such as the number of steps, direction and whether the participant is ascending or descending the staircase. The first step in developing our exercise control system is to develop an accurate steps detection and counting algorithm, which we will discuss in this section.

As we have mentioned earlier, the Apple iPhone 6s Plus is equipped with 3-axis accelerometer, 6-axis accelerometer, 3-axis gyroscope and barometer. The sensors output data frequency is very high, it is around 4000 Hz for the InvenSense 6-axes accelerometer and 8000 Hz for the InvenSense gyroscope, however, for the purpose of this study; we set the accelerometer frequency to 10 Hz.

The proposed algorithm utilizes the accelerometers to record the acceleration data of the accelerometer's x, y, and z-axis, the gyroscope to determine the walking direction and the barometer sensor data to detect ascending or descending the staircase.

In this study, we propose a step detection algorithm while ascending or descending staircase, the algorithm is composed of three phases as shown in figure 4.1:

Figure 4.1: Steps Detection Phase

Raw data Collection:

The smart mobile application sends request to the accelerometer to start sending updates of 10 Hz interval, the Tri-Accelerometer (TA) data in form of X, Y, and Z values received and stored by the application. Figure 4.2 shows a sample of the plotted accelerometer raw data while climbing the staircase.

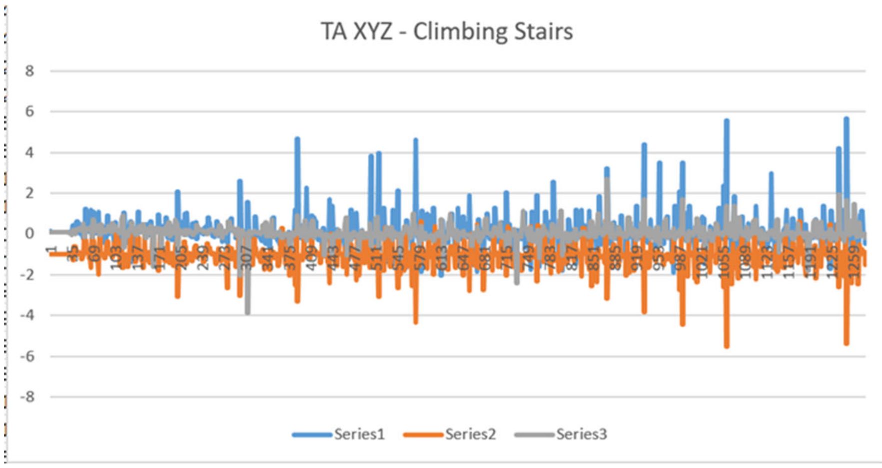


Figure 4.2: Accelerometer Raw Data

Data filtering:

Due to many factors such as sensors sensitivity, the signal needs filtering and smoothing to eliminate the noise and in order to get a higher accuracy of the number of the counted steps. The digital low pass filter that is easy to implement, requires less computational processing and has faster execution adopted in this algorithm and applied on the collected accelerometer raw data. Figure 4.3 shows the smoothed accelerometer data while climbing the staircase.

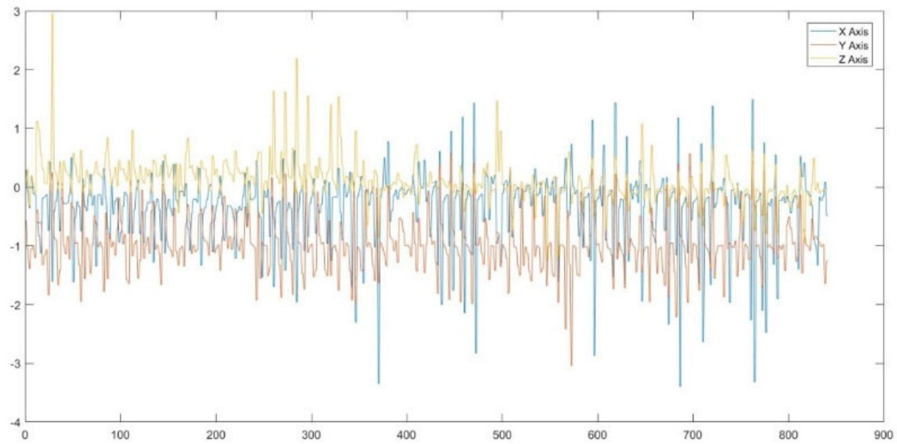


Figure 4.3: Low Pass Filter applied on TA data

Threshold detection:

Since the human movement information occurs under a frequency of 20 Hz [139], the Higher cut-off is set to 2 Hz and the Lower cut-off is set to 1 Hz. The mobile device is mounted on the ankles and the measurements can be one in three dimensions, depicted in figure 4.4, which indicates the x, y and z-axis of the accelerometer.

Figure 4.4: Smartphone fixed on ankle

It is important to mention here that the step detection algorithms can be classified according to the data processing methods such as peak detection, the correlation calculation method and the zero velocity update method. The peak detection method, which counts the steps by detecting and finding the peak on acceleration threshold.

The threshold, which represents the walking stride, varies from one to one, and we have given the user the option to set up the threshold before the exercise, however, the default threshold for this control system is 1.1 Hz.

The magnitude value of the acceleration data on the three-axis coordination is computed as the square root of the accelerometer values using equation 4.1 and then plotted as shown in figure 4.5.

$$magnitude = \sqrt{x^2 + y^2 + z^2} \qquad \text{Equation 4.1}$$

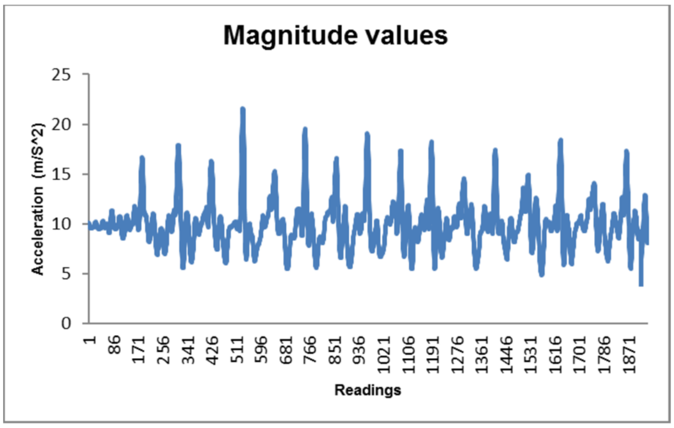


Figure 4.5: Acceleration Magnitude

The following flowchart explains the step detection algorithm.

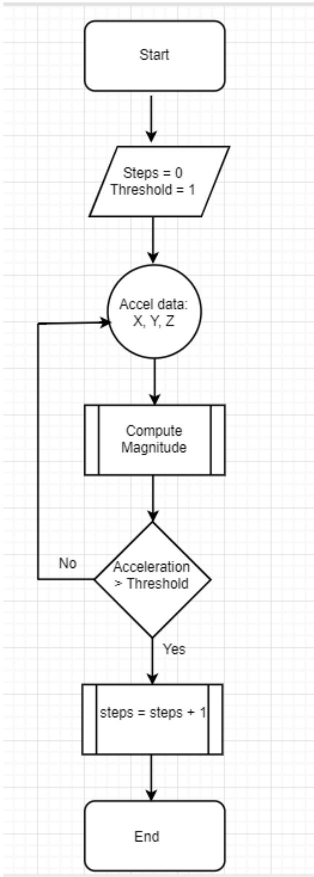


Figure 4.6: Steps Detection Flowchart

The steps detection algorithm follows the following steps to count the number of steps and other important parameters:

1. Collect the accelerometer data.
2. Compute the acceleration magnitude.
3. If the acceleration magnitude value is more than the threshold, then it is counted as a step and added to the previous steps counter.
4. If the acceleration magnitude values is less than the threshold, which means that the participant pace is slow, an alarm will be produced to notify the participant.

5. If the acceleration magnitude value is too high, which means that the participants' movement is fast, then an alarm will be produced to notify the participant.

The proposed algorithm utilizes the acceleration values of X, Y and Z-axis from accelerometer sensor, which is built in Smartphone to count steps in real-time. In our work, we assume that the mobile phone is in a static position mounted on the user ankle throughout the movements. The proposed algorithm determines the peaks precisely and each peak is assigned to one-step.

The stairs pace (number of steps while Ascending or Descending stairs per second) is another important factor to be considered in this study. The climbing stairs exercise is classified as high interval training protocol and requires a lot of efforts so we have set the ascending and descending pace as one-step per second.

The smart phone application guides the user throughout the exercise and would produce alert if the stairs pace is equal or more than two steps per second.

4.2.2 Smart Mobile Application

4.2.2.1 Overview

The smart mobile application was developed using Apple SWIFT programming language. The IDE environment as we have explained in chapter 3 is Xcode.

The Apple iPhone is equipped with many sensors such as accelerometer, gyroscope and barometer, however, before we can access these sensors, the specified sensor must be enabled and the right permission should be given by the end user, all these settings and permissions are configured on code level.

In the following section, we will give a brief description of the embedded sensors in the Apple iPhone and explain the required code to enable and access the specified sensor, how to get the sensor raw data, code to implement Low Pass Filter, and code to save and export the stored data.

4.2.2.3 Accelerometer

The Apple iPhone is equipped with a three-axis and 6-axis accelerometer, which delivers acceleration values in each of the three axes, see figure 3.6. The direction of the acceleration sets the acceleration values to either positive or negative.

The SWIFT programming language has different framework with many classes that must be enabled first to enable the sensor hardware, however, its good practice to find out if the sensor is available or not before trying to enable it.

The Apple **Core Motion** framework enables the programmer to access the raw data of the accelerometer, and the **CMMotionManager** class provides the interface for enabling the accelerometer hardware.

The following steps explain the steps required to access the Accelerometer raw data:

1. Import the Core Motion framework:

$$import\ CoreMotion$$

2. Set variable to the CMMotionManager class:

$$var\ movementManager = CMMotionManager()$$

3. Set the accelerometer update frequency:

$$movementManager.accelerometerUpdateInterval = 0.2$$

4. Start the accelerometer :

$$movementManager.startAccelerometerUpdates$$

5. The accelerometer raw data can then displayed on the application interface as following:

$$xAcceleration.text = "(acceleration.x)"$$

$$yAcceleration.text = "(acceleration.y)"$$

$$zAcceleration.text = "(acceleration.z)"$$

6. The next step is to smooth the accelerometer raw data using Low Pass Filter as we will explain in next section.

4.2.2.4 Gyroscope

The Apple iPhone is equipped with a three-axis gyroscope, which delivers orientation values in each of the three axis. Accelerometer as well as the gyroscope require the core motion framework, hence, the same steps that we have mentioned earlier work for both sensors, we just need to specify the required axis data as following:

1. Set the gyroscope update frequency:

$$movementManager.gyroUpdateInterval = 0.2$$

2. Start the gyroscope :

$$movementManager.startGyroUpdates$$

3. The gyroscope raw data can then displayed on the application interface as following:

$$xGyro.text = "(myGyroData.rotationRate.x)"$$

$$yGyro.text = "(myGyroData.rotationRate.y)"$$

$$zGyro.text = "(myGyroData.rotationRate.z)"$$

4.2.2.5 Barometer

The Apple iPhone is equipped with a powerful Altimeter that can measure the air pressure and helps in determining the altitude. Using the Altimeter, the iPhone can track any vertical movement and then we can find out i.e. how many floors were climbed during the exercise.

The following steps explain the steps required to access the Barometer raw data:

1. Import the Core Motion framework:

$$import\ CoreMotion$$

2. Set variable to the CMAltimeter class:

$$var\ altimeter = CMAltimeter()$$

3. Check if Altimeter is available in the device:

$$CMAltimeter.isRelativeAltitudeAvailable()$$

4. Start Altimeter updates:

$$altimeter.startRelativeAltitudeUpdates$$

5. Get the current altitude value and assign it to variable:

$$altitude = altitudeData!.relativeAltitude.floatValue$$

$$pressure = altitudeData!.pressure.floatValue$$

4.2.2.6 Low Pass Filter: Swift Code

The raw accelerometer data has a lot of noise and it must be processed, filtered and smoothed, using the simple digital low pass filter, the noise was eliminated as we have explained earlier in section 4.1.1. In this section, we will explain the code behind the low pass filter.

$$var\ accelerationThreshold: Double$$

$$accelerationThreshold = Double(accelerationThresholdOutlet.txt!)!$$

$$if\ \left(fabs(acceleration.x)\right) > accelerationThreshold \mid\mid \left(fabs(acceleration.y)\right) > accelerationThreshold \mid\mid \left(fabs(acceleration.z)\right) > accelerationThreshold$$

$$\{\ addstep()\}$$

In our developed system, we have set the cut-off frequency to a variable named acceleration-Threshold and this value was different from user to user because the step size varies from one to one, before performing any experiment, we have to change the threshold value to reflect the real counted step as shown in figure 4.7:

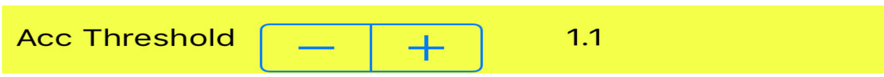


Figure 4.7: Acceleration Threshold Setting

$$@IBAction\ func\ accelerationStepperThreshold(\_\ sender: UIStepper)\{$$

$$accelerationThresholdOutlet.txt\ =\ String(sender.value)$$

4.2.2.7 Bluetooth Low Energy Connection

The Apple iPhone 6s Plus can communicate with devices that are equipped with BLE technology. The Core Bluetooth framework provides the classes that are required by the developed application to communicate with BLE devices.

The following steps explain the steps required to enable BLE devices communications with SWIFT application:

1. Import the Bluetooth Core framework:

$$import\ CoreBluetooth$$

2. Delegate classes to the application:

$$class\ ViewController: UIViewController, CBCentralmanagerController, CBPeripheralDelegate$$

3. Set Bluetooth variables:

$$var\ centralBTManager: CBCentralManager!$$

$$var\ connectioBTPeripheral: CBPeripheral!$$

4. Set the heart rate sensor service ID to 180D:

$$if\ service.uuid == CBUUID(string: "180D")$$

5. Measure the heart rate value:

$$acualMeasuredBpm = \ heartRateValue.count"$$

6. Display the measured heart rate value on the application:

$$hrOutlet.text = String(acualMeasuredBpm)$$

4.2.2.8 Voice Commands

The voice commands provide users with easy way to respond to the exercise intensity. In this control system, we have used both the audio stimulation such as beeps and voice commands such as “Go Up”. The user just need to respond to either the audio beep or voice commands to maintain the exercise intensity and to know when to start or stop the exercise.

The audio beeps are utilizing the built in system sounds to notify the user of starting and ending of the exercise, in addition to maintain the walking speed, i.e if the user is climbing the stairs very fast, the system will produce a beep. The code to enable the system built in beep is shown below:

$$AudioServicesPlayAlertSound(1002)$$

However, to enable voice commands, the SwiftySound [140] library used in our control system. Using the Cocoa Pods which is a dependency manager we have installed the SwiftySound library in our application. The following code will run when the participant reaches 80% of his HR_{max}:

$$Sound.play(file\text{: "}Down.wav\text{"})$$

When the user reaches 60% of his HR_{max}, the following command will be enabled and the user is required to respond accordingly and start climbing the stairs again:

$$Sound.play(file\text{: "}Up.wav\text{"})$$

There are a few voice commands as mentioned, in addition to voice commands to start and finish the exercise.

4.2.2.9 Data Manipulation

It is very important for the smart phone control system to store the collected data locally, for this purpose, the Apple Core Data framework that manage the model layer objects in the application. In Xcode environment, the xcdatamodeld file in the application serves as a database table and the attributes are the table entries. Figure 4.8 shows the table entries, which we have defined and used in this application to store the collected data such as the accelerometer, HR, steps, and direction data.

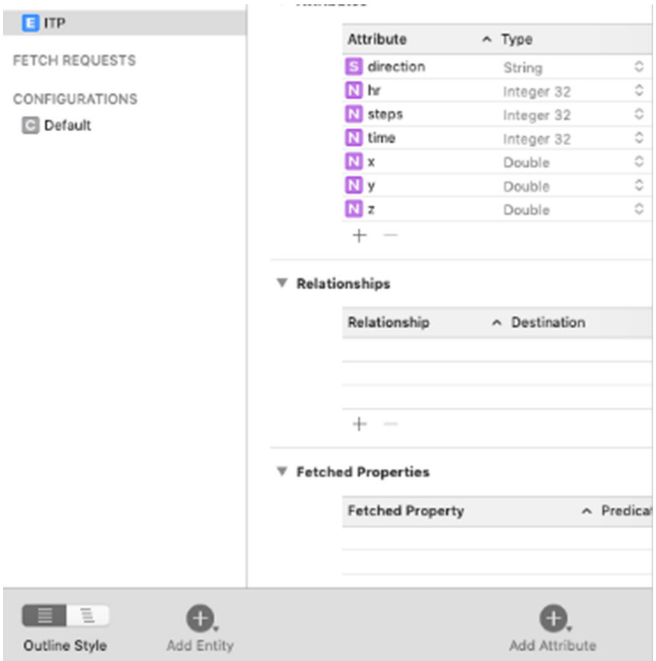


Figure 4.8:Xcode Core Data attributes

Part of the code to store and export the collected data is explained here, while the full code is provided as appendix:

1. Import the Core Data framework:

$$import\ CoreData$$

2. Define the database name:

$let\ controlsystemData$
$= \ NSEntityDescription.insertNewObject(forEntityName: "ITP, into: managedObjectCon$

3. Assign data to table entries:

$controlsystemData.SetValue(Double(xAcceleration.text!), forkey: "x")$

$controlsystemData.SetValue(Double(yAcceleration.text!), forkey: "y")$

$controlsystemData.SetValue(Double(zAcceleration.text!), forkey: "z")$

$controlsystemData.SetValue(Double(stepsCounted.text!), forkey: "steps")$

$controlsystemData.SetValue(Double(heartrate.text!), forkey: "hr")$

$controlsystemData.SetValue(String(directioninfo.text!), forkey: "direction")$

The user have the option at the end of the exercise to export data as shown in figure 4.9:

Figure 4.9: Export data Menu

4.2.2.10 Application Flowchart

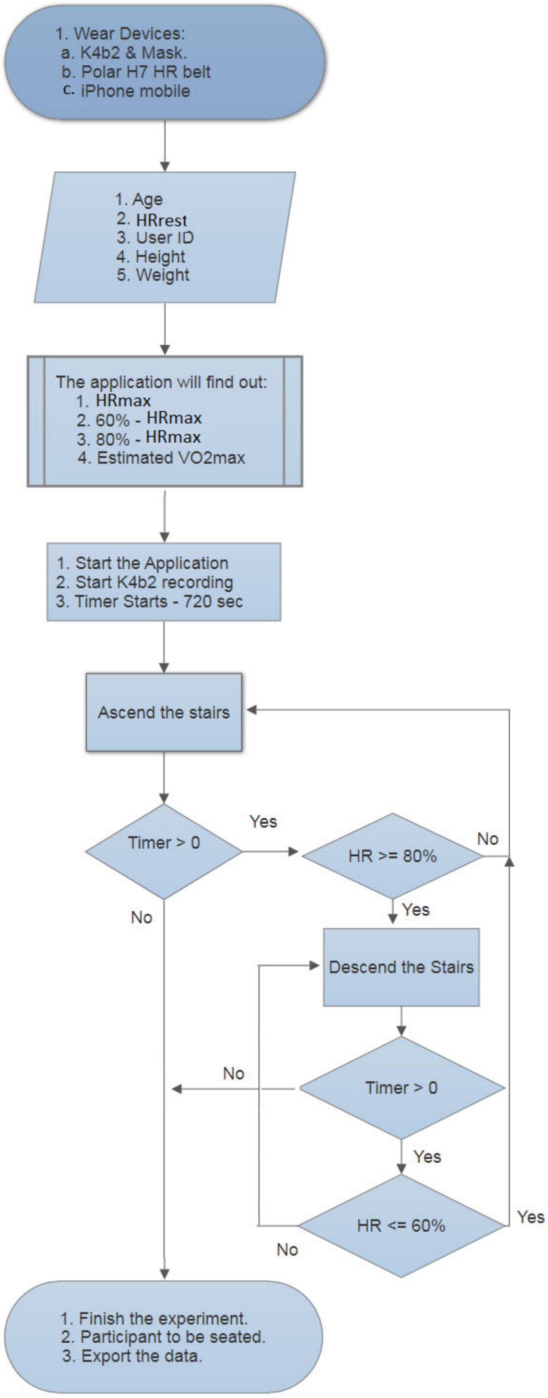


Figure 4.10: Application Flowchart

4.3 TI eZ430-Chronos Watch Control System

The eZ430-Chronos watch from Texas Instruments is a complete development system featuring a 96-segment LCD display, an integrated pressure sensor, and a three-axis accelerometer for motion sensitive control [131]. The integrated wireless interface allows the eZ430-Chronos to act as a central hub for nearby wireless sensors such as pedometers and heart-rate monitors. The eZ430-Chronos offers temperature and battery voltage measurement and is complete with a USB-based MSP430F5509 + CC1101 (part of the new eZ430-Chronos kit with white PCBs) or CC1111 (part of the initial eZ430- Chronos kit with black PCBs) wireless interface to a PC.

The steps detection algorithm, which explained earlier, was used and implemented in the eZ430-Chronos watch. The algorithm utilizes the integrated 3-axes accelerometer to detect the number of steps and find the user direction. In addition, the watch connects through BlueRobin protocol to heart rate sensor to monitor and control the exercise intensity.

The following figure shows the heart rate code in CCS which has been written in C++ language and later on were uploaded to the watch.

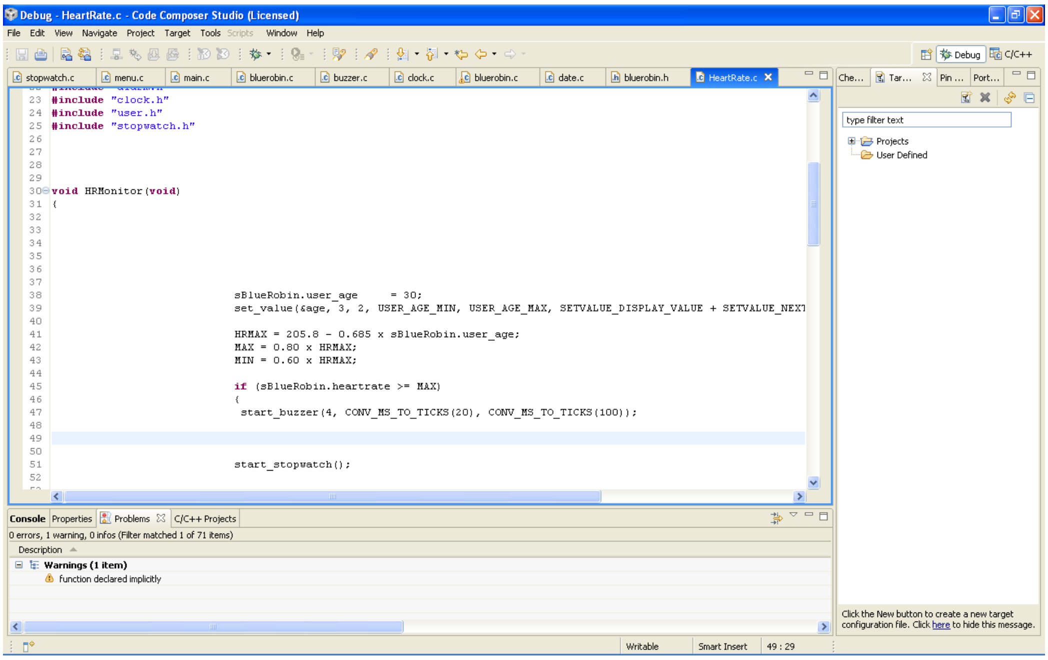


Figure 4.11: CCS -Heart Rate Code

The whole firmware was then debugged in the CCS and uploaded to the eZ430-Chronos watch without any errors as shown in the following figure:

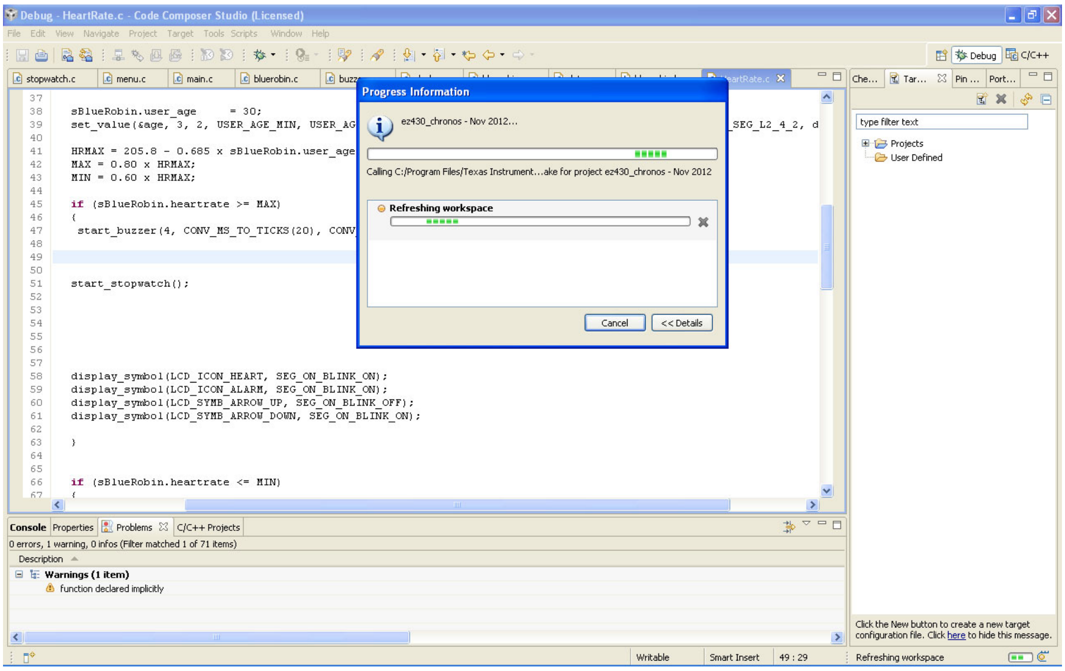


Figure 4.12: CCS - Debug Project

After loading the code into the eZ430-Chronos watch without any errors, the watch has been assembled again and is ready to be used by patients.

4.4 Conclusion

The training and rehabilitation control system utilizes the built-in sensors in the smartphone and in the TI eZ430-Chronos watch to increase the athletes' cardiovascular fitness system and to help the cardiac patients with their outpatient rehabilitation program by using portable devices.

The control system was deployed on Apple iPhone as an application, and on TI ez430-Chronos watch to monitor and control the exercise intensity and guide the user throughout the exercise through voice and audio commands.

Chapter 5 : Experiments

5.1 Overview

In this study, we have utilized the UTS emergency exit of building one as an outdoor exercise environment to carry out our experiments. Ten volunteers were asked to ascend and descend stairs while monitoring their heart rate to maintain the exercise intensity. The collected data was divided into two datasets, one dataset is used for system identification, and estimation of the models' parameters and the other dataset is used for validating the estimated models.

5.2 Volunteers

Ten untrained but healthy non-smoking males participated in the experiments that involves ascending and descending the staircase for twelve minutes. The characteristics of the volunteers who participated in this study shown in Table 5.1.

Table 5.1: Participants'' characteristics'

Subjects	Age (Yr)	Height (cm)	Weight (Kg)
1	25	168	73
2	27	174	75
3	30	177	72
4	33	168	74
5	38	172	65
6	26	180	70
7	45	165	80
8	43	168	73
9	40	165	70
10	24	172	75

The subjects were free from any known medical condition and were not under any medication. The experiments procedures and any potential risks that might involve during the experiments were explained in details. The participants were informed that they have to stop the experiment at any time they feel uncomfortable for any reason such as fatigue or breath difficulties. The University of Technology Sydney (UTS) approved the study and an informed consent was obtained from all participants before each experiment.

5.3 Experiment Location

The emergency stairs of building one, University of Technology, Sydney (UTS) was chosen to carry out all the experiments. The emergency exit stairs of building one consists of two flights of stairs of the 28 levels, each flight contains 11 steps, which is 22 steps per level. The stairs measurements is shown in Figure 5.1.

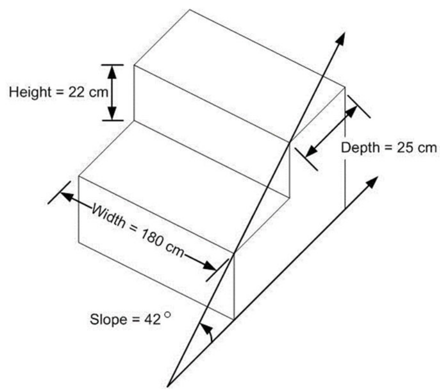


Figure 5.1: UTS Staircase

All experiments were conducted at the same hour of the day between 11:00 AM and 1:00 PM. The temperature was measured to be around 20◦ Celsius, and the humidity was set at approximately 50%. The emergency exit has acceptable efficient air ventilation and all location attributes did assure that all equipment were operating under normal environmental temperatures and conditions.

The participants were required to start climbing stairs from level 12 all the way up until they reach 80% of their HR_{max} which is considered as onset exercise, and then the participants' are required to descend the stairs until they reach 60% of their HR_{max} is considered as offset exercise.

Each participant were required to wear the Cosmed K4b^2, eZ430-Chronos watch, HR belts and Apple iPhone as shown in Figure 5.2:

Figure 5.2: Participants wearing devices

5.4 Experiment Protocol and Setup

Stairs climbing exercise is one form of an outdoor exercises that is available for free anywhere, in this study, we have adopted the stairs climbing exercise to control and model the exerciser intensity based on the heart rate and to build exercise and rehabilitation monitory system.

Each experimental exercise consists of three different phases, i.e., warm up, exercising and recovery as shown in figure 5.3. The training period also called onset exercise, while the recovery period called offset exercise. The onset exercise in our case is climbing the stairs, and descending the stairs is the offset exercise.

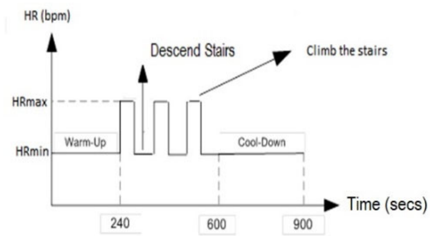


Figure 5.3: Stairs Climbing Exercise Protocol

Warm up Phase:
During the warm up phase which is the first 180 seconds of the exercise, the HR were obtained and recorded by the smartphone application and the average of the obtained HR values were set as resting HR (HR_{rest}) which is a very important indicator of our cardiovascular fitness system health.

Exercise Phase:
The exercise phase lasts for 12 minutes and the intensity of the exercise was based on the HR values. The subjects were asked to switch between high intensity exercise, which is in this case climbing the stairs, and low intensity exercise, which is descending the staircase.

Recovery Phase:

The recovery phase is a vital phase that prevent any injury after exercising and helps the muscle to return to its normal condition. The recovery phase lasts for five minutes and the HR recovers to its HR_{rest}.

As we have mentioned earlier, that the Maximum Heart Rate (HR_{max}) is defined as the highest number of beats per minute (bpm) during maximum exertion. There are many formulas to calculate the HR_{max}; the easiest and most common method is by using this formula:

$$\mathbf{HR_{max} = 220 - Age} \qquad \text{Equation 5.1}$$

However, in this study, the Inbar [41] formula was adopted to find out the HR_{max} for each participant. i.e. the HR_{max} for the subject whose age is 43 is calculated as following:

$$\mathbf{HR_{max} = 205.8 - 0.685\ x\ (age)} \qquad \text{Equation 5.2}$$

$$= 205.8 - 0.685\, x\, 43$$
$$= 176.345$$
$$\approx 176\ bpm$$

The subjects HR_{max} have been calculated based on Equation 8. The following table shows the recommended HR_{max} for each participant along with the low and high intensity exercise:

Table 5.2: Participants Training Zone

Subjects	Age (yr)	HR_{max}	Low Intensity Exercise (60% of HR_{max})	High Intensity Exercise (80% of HR_{max})
1	25	189	113	151
2	27	187	112	150
3	30	185	111	148
4	33	183	110	147
5	38	180	108	144
6	26	188	113	150
7	45	175	105	140
8	43	176	106	141
9	40	178	107	143
10	24	189	114	151

Before starting the experiment, the following information is required in order to find out the HR_{max} and other vital information:

1. User name.
2. User Age.
3. Exercise ID.
4. Date.

Based on the above information the smart phone application guides the athletes during the stair climbing exercise through voice commands and alerts. Figure 5.4 shows a snap shot of the smart mobile application where the user enter his basic information before starting any exercise.

Figure 5.4: Smartphone Application Interface

Once, the basic participant data provided, the smart phone application calculates the HR_{max}, onset and offset recommended HR.

Each participant wore the Cosmed K4b^2, a portable indirect calorimetry system, while climbing the stairs. The Cosmed K4b^2 has been shown to be a valid instrument to measure oxygen consumption for a wide range of work rates on a cycle ergometer.

The portable indirect calorimetry unit was mounted on the participant via a chest harness. A flexible facemask that covered the participant's mouth and nose was attached. The facemask was secured to the participant via a head strap as shown in Figure. 5.5

Figure 5.5: K4b2 unit Facemask

The Cosmed K4b^2 portable metabolic system was calibrated as per manufacturer instructions, after the calibration process was completed, participants information such as gender, age, height, and weight were entered into the Cosmed K4b^2 portable system as shown in Figure 5.6:

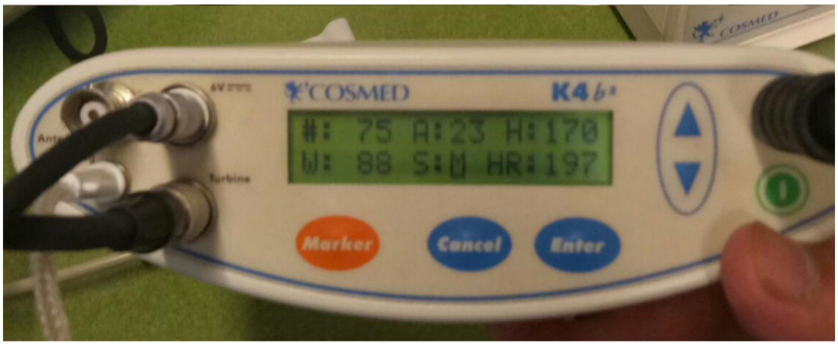


Figure 5.6: K4b^2 PU - User Information

Data from the portable Cosmed K4b^2 that is stored locally has been downloaded to a Windows-based personal computer after the test was completed.

COSMED K4b^2 have been calibrated and the subjects data entered, before starting any test, and after finishing the test, the systems need to be stopped and then the data to be transferred through the companion software to the computer for further analysis.

Having all the required tools turned on, calibrated and having the required subjects' data such as ID and age, the experiment starts in the following procedures:

- Sit on chair and rest for two minutes before starting the exercise.
- Stand up and wait for two minutes.
- Starts walking on the flat platform for three minutes.
- Starts climbing the stairs on normal pace.

- The smart mobile application produces a voice command “Go Down” once the participant has reached 80% of his HR_{max}.
- Subject needs to respond to the voice command by descending the staircase.
- The smart mobile application produces a voice command “Go Up” once the participant has reached 60% of his HR_{max}.
- Subject needs to respond to the voice command by ascending the staircase.
- The smart mobile application will monitor the ascending/descending pace, and notify the participant by producing alert to either increase or decrease his pace.
- The exercise lasts for 12 minutes.

A voice notification “***Exercise Ends***” will be produced at the end of exercise. Subject will be seated on a chair and relax for five minutes.

5.5 Experiments data and results

All the experimental exercise data were collected using the Cosmed $K4b^2$ device and the smartphone application. The Cosmed $K4b^2$ data were transferred to the PC desktop using the serial connection RS-232 port, while the smartphone data were transferred to a laptop through Bluetooth connection. In the next sections, we will explain the collected data type and structures.

5.5.1 Cosmed $K4b^2$ data

During the experiments, the Cosmed $K4b^2$ stores the collected participants’ physiological parameters such as VO_2 and VCO_2 locally and then we can download them using the

K4b[2] application to desktop using the RS-232 cable for further data analysis. Figure 5.7 shows a sample of the exported file.

D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	
Test number:	95		Barometric press. (mmHg):	766		t	Rf	VT	VE	VO2	VCO2	O2exp	CO2exp	VE/VO2	VE/VCO2	VO
Test date:	16/05/2018		Temperature (degrees C):	25		hh:mm:ss	b/min	l	l/min	ml/min	ml/min	ml	ml	---	---	ml/
Test time:	11:35		Humidity;%	50												
N. of steps:	311		Temp. flowm. (degrees C):	34		00:00:02	21.2766	0.941315	20.02797	761.9833	522.748	156.8518	29.7794	26.284	38.31286	8.9
Duration (hh:mm:ss):	00:12:26		Humidity flowm.;%	100		00:00:04	22.38806	0.867886	19.43028	746.0189	518.1389	144.2057	28.04567	26.04529	37.50014	8.7
BSA (m^2):	1.973747		STPD:	0.833052		00:00:07	23.62205	1.050438	24.81349	866.9778	654.0001	178.0645	33.55282	28.62068	37.94111	10
BMI (Kg/m^2):	29.06877		BTPS insp:	1.091195		00:00:10	19.60784	1.999911	39.21394	1485.025	1197.852	331.3468	73.93858	26.40625	32.73688	17
HR max (bpm):	197		BTPS exp:	1.019842		00:00:12	25.42373	1.494069	37.98481	1428.201	1139.515	248.1277	54.25562	26.59626	33.33418	16
			UN (g/day):	0		00:00:14	31.91489	1.125906	35.93317	1044.529	855.9094	197.8494	32.53297	34.4013	41.98245	12
			AMR (Kcal/day)	0		00:00:15	37.5	1.259505	47.23145	1477.737	1249.756	217.8384	40.38576	31.96201	37.79253	17
			VD (ml):	0		00:00:18	27.77778	1.326815	36.85597	1230.577	1033.827	226.303	45.07704	29.95015	35.65003	14
			LT:	--:--:--		00:00:20	28.30189	1.354351	38.33068	1298.967	1072.367	230.3824	45.89291	29.5086	35.74401	15
			RC:	--:--:--		00:00:22	25.31646	1.301319	32.94478	1191.087	963.8778	218.1443	46.09688	27.65942	34.17942	14
			FEV1 (l):	0		00:00:25	22.98851	1.291121	29.68093	1194.602	896.7601	211.1074	47.21871	24.84588	33.09796	14
			FEV1 (l):	0		00:00:27	23.90438	1.369648	32.7406	1502.521	988.8217	216.6145	50.07427	21.79044	33.11072	17
			FVC (l):	0		00:00:29	29.26829	1.419621	41.54987	1875.969	1222.764	225.7931	50.58419	22.14848	33.9803	22
			FVC (l):	0		00:00:32	26.20087	1.764327	46.22692	2153.754	1412.851	277.7031	65.26992	21.46341	32.7189	25
			MVV (l/min):	0		00:00:34	24.09639	1.587895	38.26252	1858.14	1204.222	246.5979	60.47666	20.59184	31.77365	21
			MVV (l/min):	0		00:00:36	25.53191	1.543022	39.3963	2023.38	1276.233	235.1757	60.47666	19.47054	30.86921	23
			IC (l):	0		00:00:39	22.64151	2.041725	46.22773	2372.012	1527.058	310.95	81.5874	19.48882	30.27241	27
			IC (l):	0		00:00:41	27.90698	1.610331	44.93948	2202.515	1396.857	249.5555	60.57864	20.40371	32.17186	25
			VO2max (ml/min):	0		00:00:43	26.08696	1.769427	46.15896	2349.285	1495.292	270.4622	69.34929	19.64809	30.86953	27

Figure 5.7: K4b[2] device - User Exported Data

Figure 5.8 shows the plotted physiological parameters, the volume of oxygen (VO_2) of participants' one while ascending and descending the staircase in day 1 and day 7.

Comparing the results of VO_2max of day 1 and day 7 suggests increasing of VO_2max by 8%, however, more experiments are required to carry out on more volunteers to prove that the stairclimbing exercise can improve the participants' VO_2max and the percentage of the improvements.

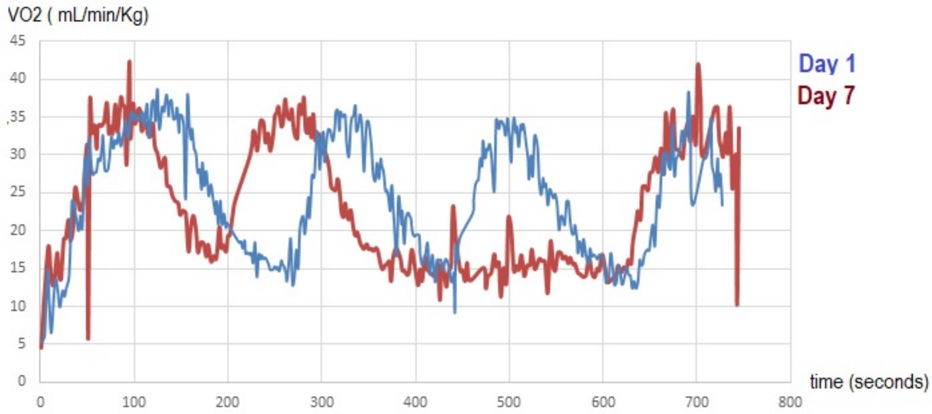


Figure 5.8: VO_2 - participant 1 - Day 1 and Day 7

5.5.2 Smartphone Application data

The Apple iPhone application stores the collected data using CoreData technology. The collected data can then be transferred using Bluetooth connection or by e-mail. Figure 5.8 shows a sample of collected data while exercising.

Time	X	Y	Z	Steps	HR	Direction
1	-0.30608	0.252411	0.208954	1	83	Ascending
1	0.134949	-1.0031	0.128937	1	83	Ascending
1	0.134949	-1.0031	0.128937	2	83	Ascending
1	-0.04265	-1.01927	0.062378	2	83	Ascending
1	-0.04265	-1.01927	0.062378	2	83	Ascending
1	-0.32199	-1.56641	0.09581	2	83	Ascending
1	-0.32199	-1.56641	0.09581	2	83	Ascending
1	-0.05994	-0.31956	0.697876	2	83	Ascending
1	-0.05994	-0.31956	0.697876	2	83	Ascending
1	0.808075	-1.65852	0.886765	2	83	Ascending
2	0.808075	-1.65852	0.886765	2	83	Ascending
2	1.030167	-1.0323	-0.64523	2	83	Ascending
2	1.030167	-1.0323	-0.64523	2	83	Ascending
2	0.056824	-1.01447	0.06958	2	83	Ascending
2	0.056824	-1.01447	0.06958	2	83	Ascending
2	0.107376	-1.04111	0.08876	2	83	Ascending
2	0.107376	-1.04111	0.08876	3	83	Ascending
2	-0.41721	-1.6248	-0.07262	3	83	Ascending
2	-0.41721	-1.6248	-0.07262	3	83	Ascending
2	0.10376	-1.01877	0.254944	3	84	Ascending
3	0.10376	-1.01877	0.254944	3	84	Ascending

Figure 5.9: Smartphone Application Collected Data Sample

The heart rate is recorded beat by beat and the following figure shows the plot of HR vs Time during ascending and descending the stairs.

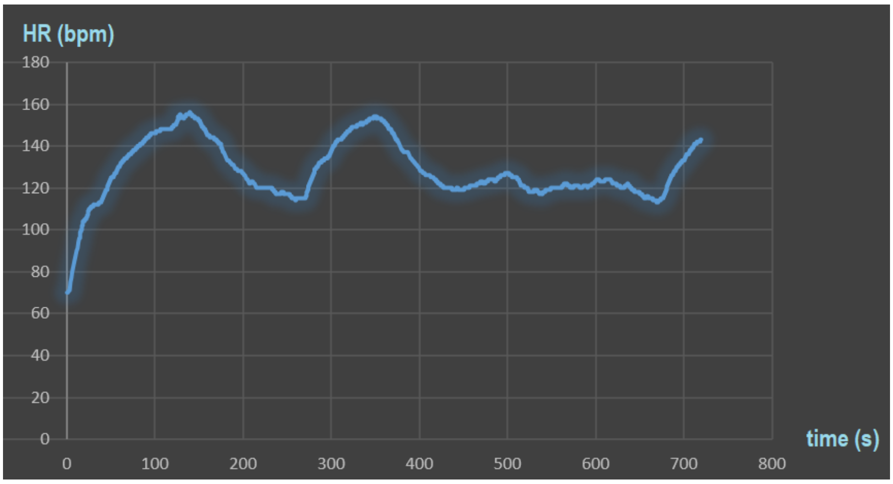


Figure 5.10: HR vs Time

5.6 Conclusion

The volunteers performed more than twenty experiments that involve ascending or descending staircase while equipped with $K4b^2$ device, Apple iPhone 6s Plus, and heart rate sensors. The $K4b^2$ device stored data locally and then transferred to a desktop computer through RS-232 cable, while the iPhone data stored locally and transferred using the BLE connection to the computer at the end of each exercise.

Chapter 6 : Modelling of Tri-axial Accelerometers in a self-Designed Wearable IMU

6.1 Overview

Micro Inertial measurement units (μ-IMU) have been extensively used in vehicle navigation, posture detection, gesture recognition, and exercise/health monitoring [141], [142]. μ-IMU commonly includes orthogonally tri-axial accelerometers and gyroscopes, which measure acceleration and angular velocity [141].

Due to its structural simplicity, operational convenience and high reliability, μ-IMUs are used to create low-cost, high- accuracy, high sensitivity measurement systems [143], [144]. With the recent developments on MENS technology, Micro IMU is gradually taking the roles of traditional IMU. For example, μ- IMUs have recently been applied in flight stabilization of autonomous hovering of helicopters and quad-rotors [145]. Due to its small size and light-weight, μ-IMUs have also been integrated on cloth or shoes for monitoring human's motion [145] (e.g. gait analysis). Since 2005, μ-IMUs have mushroomed in mobile device markets [146, 147, 148]. Under the consideration of its growing popularity, we have developed a new device that integrates μ-IMU systems in capturing patients' motion for gait analysis and fall prediction.

Although Micro-IMUs are quite reliable, the output of accelerometers, however, contains various errors [149]. The performance of the accelerometer is often affected by several factors, which include imperfections due to improper manufacturing procedures [150], sensitivities to temperature variations, other external factors [151], and also the coupling with other sensors. A properly selected calibration method can directly improve the performance of μ-IMU. Generally, most calibration methods require certain advanced laboratory equipment such as a turntable, vibration generator and/or optical tracking systems. Sometimes robotic actuation is applied to assist calibration [152]. The most commonly used calibration method is to align each axis of the accelerometer to known reference accelerations, for example, gravity acceleration, and estimate parameters according to the reference acceleration [149]. However, this classical approach is attitude dependent. The labs in a university often have no such kind of technical equipment (e.g., six degrees of freedom manipulator) that can provide high accuracy acceleration reference. Another popular calibration approach is the so called auto-calibration which does not require any accurate acceleration references. Making a comparison and selecting a suitable calibration method thus has a significant impact on the development of the self-designed portable sensor. Consequently, these two calibration methods, auto-calibration and the slightly revised classical calibration method, have been selected for comparison study.

6.2 Calibration Methods

6.2.1 Auto Calibration Method

Before the slightly modified classical calibration method is introduced, we give a brief discussion of the auto calibration method whose detailed descriptions have been well reported in literature [143]. As stated by [143] the auto-calibration method is based on the basic fact that the acceleration module which is measured by 3- axis accelerometer should equal to the local gravity acceleration “1g” in static condition [142, 152, 149]. The established framework is illustrated in Figure 6.1.

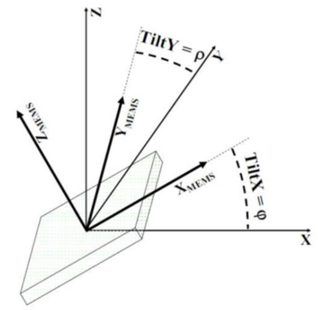


Figure 6.1: φ is the angle of the MEMS accelerometer in x direction with absolute XY plane. ρ is the angle of MEMS accelerometer y direction with absolute XY plane.

To find the best fitting parameters, they compare the angle between the X-axis and XY plane, Y-axis and the XY plane that to assess the performance of their calibration. The basic principle of the auto-calibration is:

$$\boldsymbol{g} = \sqrt{\boldsymbol{a_x^2} + \boldsymbol{a_y^2} + \boldsymbol{a_z^2}} \qquad \text{Equation 6.1}$$

We select the 6-parameter model as follows:

$$\begin{cases} \boldsymbol{a_x} = \boldsymbol{S_{xx}} \cdot (\boldsymbol{V_x} - \boldsymbol{O_x}) \\ \boldsymbol{a_y} = \boldsymbol{S_{yy}} \cdot (\boldsymbol{V_y} - \boldsymbol{O_y}) \\ \boldsymbol{a_z} = \boldsymbol{S_{zz}} \cdot (\boldsymbol{V_z} - \boldsymbol{O_z}) \end{cases} \quad \boldsymbol{\ldots\ldots} \qquad \text{Equation 6.2}$$

In order to determine the 6 fitting parameters, S_{xx} , S_{yy} , S_{zz} , O_x , O_y , O_z the 3-axis readings of IMU under N different random postures are recorded [143]. These readings are regarded as known parameters V_x , V_y , V_z in (6.2). [143] uses the Nonlinear Least Squares Method to determine the other six unknown parameters. The index function, the sum of squares (E) and errors (e) are defined as follows:

$$\boldsymbol{e_i} = \sum \boldsymbol{j} = \boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z} \left\{ \left[\boldsymbol{S_{ij}} \cdot (\boldsymbol{V_{j,i}} - \boldsymbol{O_j}) \right]^2 \right\} - \boldsymbol{g^2} \quad \ldots \text{ Equation 6.3}$$

$$\boldsymbol{E} = \sum_{i=1}^{N} \boldsymbol{e_i^2} \quad \ldots \qquad \text{Equation 6.4}$$

Where S_{ij} is the sensitivity of each direction and O_j is the offset and $V_{j,i}$ is the ADC values obtained from the Micro-IMU. [143] points out that Newton method could be minimizing procedure [143]:

$$\boldsymbol{X_{n+1}} = \boldsymbol{X_n} - \propto . \boldsymbol{H^{-1}}(\boldsymbol{X_n}) . \boldsymbol{J}(\boldsymbol{X_n}) \quad \ldots \qquad \text{Equation 6.5}$$

Where X_n is the vector of iteration for nth that contains $S_{xx}, S_{yy}, S_{zz}, O_x, O_y, O_z$ as parameters and $H(X_n)$ and $J(X_n)$ are Hessian matrix and Jacobian vector respectively and α is a coefficient that less than 1 [143].

$$\boldsymbol{J}(\boldsymbol{X_n}) = \begin{bmatrix} \frac{\partial E}{\partial X_1} & \frac{\partial E}{\partial X_2} & \cdots & \frac{\partial E}{\partial X_n} \end{bmatrix} \quad \ldots \qquad \text{Equation 6.6}$$

$$\boldsymbol{H}(\boldsymbol{X_n}) = \begin{bmatrix} \frac{\partial^2 E}{\partial X_1^2} & \frac{\partial^2 E}{\partial X_1 \partial X_2} & \cdots & \frac{\partial^2 E}{\partial X_1 \partial X_n} \\ \vdots & & \ddots & \vdots \\ \frac{\partial^2 E}{\partial X_n \partial X_1} & \frac{\partial^2 E}{\partial X_n \partial X_2} & \cdots & \frac{\partial^2 E}{\partial X_n^2} \end{bmatrix} \quad \ldots \qquad \text{Equation 6.7}$$

This procedure will terminate until the condition is satisfied by:

$$\boldsymbol{max} \left\{ \left| \frac{x_k^n - x_k^{n-1}}{x_k^n + x_k^{n-1} / 2} \right| \right\} < \boldsymbol{\varepsilon} \ldots \qquad \text{Equation 6.8}$$

where x_k^n is the k^{th} element in x_n, S_{xx} is x_1^n, and ε equals to $1.5 \, X \, 10^{-6}$ [143]. After the completion of the minimum [143] returns these six parameters to equation (2) and accelerations, a_x, a_y, a_z can be calculated through experimental ADC values, V_x, V_y, V_z. After the process of the calculation of fitting parameters, [143] detected orientation using equation (6.9) as following:

$$\begin{cases} \varphi = \mathbf{arctan} \frac{a_x}{{}^{(1)}\sqrt{a_y^2 + a_z^2}} \\ \rho = \mathbf{arctan} \frac{a_y}{\sqrt{a_x^2 + a_z^2}} \end{cases} \quad \ldots. \qquad \text{Equation 6.9}$$

In the final part of their paper, [143] analysed the results of experiment that he believed this approach is feasible due to the fact that φ and ρ never exceed $2°$ [143]. Because equation (6.2) is a typical auto calibration model, we select this 6-parameter model as an auto calibration model in our comparison study. A new but more standard and simple linear auto-calibration model can be established based on (2):

$$\begin{cases} a_{x=S_x \cdot V_x + O_x} \\ a_{y=S_y \cdot V_y + O_y} \\ a_{z=S_z \cdot V_z + O_z} \end{cases} \quad \ldots \qquad \text{Equation 6.10}$$

Based on equation (3) and (4), define the errors under unit "g" as follows:

$$\boldsymbol{e_i = \sum j = x, y, z \{(S_{jj} \cdot V_{j,i} - O_j{}^2) - 1^2} \qquad \ldots \qquad \text{Equation 6.11}$$

$$\boldsymbol{E = \sum_{i=1}^{N} e_i^2} \quad \ldots \qquad \text{Equation 6.12}$$

Convert equations (6.11) and (6.12) to a more detailed format:

$$\boldsymbol{e_i} = \left(\begin{bmatrix} V_{xi} & 0 & 0 \\ 0 & V_{yi} & 0 \\ 0 & 0 & V_{zi} \end{bmatrix} \begin{bmatrix} S_x \\ S_y \\ S_z \end{bmatrix} + \begin{bmatrix} O_x \\ O_y \\ O_z \end{bmatrix} \right)^T \cdot \left(\begin{bmatrix} V_{xi} & 0 & 0 \\ 0 & V_{yi} & 0 \\ 0 & 0 & V_{zi} \end{bmatrix} \begin{bmatrix} S_x \\ S_y \\ S_z \end{bmatrix} + \begin{bmatrix} O_x \\ O_y \\ O_z \end{bmatrix} \right) - \mathbf{1^2} \ldots \text{Equation 6.13}$$

$$\boldsymbol{E} = \sum_{i=1}^{N} \left(\left(\begin{bmatrix} V_{xi} & O & O \\ O & V_{yi} & O \\ O & O & V_{zi} \end{bmatrix} \begin{bmatrix} S_x \\ S_y \\ S_z \end{bmatrix} + \begin{bmatrix} O_x \\ O_y \\ O_z \end{bmatrix} \right)^T \cdot \left(\begin{bmatrix} V_{xi} & O & O \\ O & V_{yi} & O \\ O & O & V_{zi} \end{bmatrix} \begin{bmatrix} S_x \\ S_y \\ S_z \end{bmatrix} + \begin{bmatrix} O_x \\ O_y \\ O_z \end{bmatrix} \right) - \mathbf{1^2} \right)^2 \ldots \text{Equation 6.14}$$

One of the possible ways to minimize is by use of the Nonlinear Least Square Method, because the error function (equation 6.14) is a non-linear system. The basic principle of Nonlinear Least Square Method is the unconstrained minimization problem [153]. Its mathematical expression is:

$$\boldsymbol{min\, f(X) \; = \; \sum_{i=1}^{n} f_i(X)^2} \qquad \ldots \qquad \text{Equation 6.15}$$

In model (equation 6.15), $f(X)$ is E and $f_i(X)$ is e_i which are illustrated in equation (6.11) and (6.12) respectively. The function/command $lsqnonlin$ in Matlab solves nonlinear least square problem and nonlinear data fitting problem. Using this function, we have to find proper initial values for parameters to ensure its convergence.

6.2.2 Classical Calibration Method

Classical calibration methods require the direction of accelerometer axe to align accurately respective to the local gravity, such as aligning X negative direction to the local gravity and recording the ADC value as "-1g"; aligning X positive direction with local gravity and recording the ADC value as "1g" thereafter. Then, the following equations can be obtained:

$$\boldsymbol{\begin{cases} V_{xp}S_x + O_x = 1 \\ V_{xn}S_x + O_x = -1 \end{cases}} \qquad \ldots \qquad \text{Equation 6.16}$$

Every group equation represents different axis, *X, Y, Z*. The matrix formats of these functions are:

$$\boldsymbol{\begin{cases} V_{yp}S_y + O_y = 1 \\ V_{yn}S_y + O_y = -1 \end{cases}} \qquad \ldots.. \qquad \text{Equation 6.17}$$

$$\begin{cases} \boldsymbol{V_{zp}S_z + O_z = 1} \\ \boldsymbol{V_{zn}S_z + O_z = -1} \end{cases} \quad \dots \quad \text{Equation 6.18}$$

Every group equation represents different axis, *X, Y, Z*. The matrix formats of these functions are:

$$\begin{bmatrix} \boldsymbol{V_{xn}} & \boldsymbol{1} \\ \boldsymbol{V_{xp}} & \boldsymbol{1} \end{bmatrix} \begin{bmatrix} \boldsymbol{S_x} \\ \boldsymbol{O_x} \end{bmatrix} = \begin{bmatrix} \boldsymbol{-1} \\ \boldsymbol{1} \end{bmatrix} \quad \dots \quad \text{Equation 6.19}$$

$$\begin{bmatrix} \boldsymbol{V_{yn}} & \boldsymbol{1} \\ \boldsymbol{V_{yp}} & \boldsymbol{1} \end{bmatrix} \begin{bmatrix} \boldsymbol{S_y} \\ \boldsymbol{O_y} \end{bmatrix} = \begin{bmatrix} \boldsymbol{-1} \\ \boldsymbol{1} \end{bmatrix} \dots \quad \text{Equation 6.20}$$

$$\begin{bmatrix} \boldsymbol{V_{zn}} & \boldsymbol{1} \\ \boldsymbol{V_{zp}} & \boldsymbol{1} \end{bmatrix} \begin{bmatrix} \boldsymbol{S_z} \\ \boldsymbol{O_z} \end{bmatrix} = \begin{bmatrix} \boldsymbol{-1} \\ \boldsymbol{1} \end{bmatrix} \quad \dots \quad \text{Equation 6.21}$$

In order to minimize the random errors, all ADC values which obtained from every direction should be converted to mean value. That is to say, for example, all ADC values recorded in X positive direction will be calculated as a mean value, recorded as V_{xp} .

Generally, the matrices $\begin{bmatrix} V_{xn} & 1 \\ V_{xp} & 1 \end{bmatrix}$, $\begin{bmatrix} V_{yn} & 1 \\ V_{yp} & 1 \end{bmatrix}$ and $\begin{bmatrix} V_{zn} & 1 \\ V_{zp} & 1 \end{bmatrix}$ are square and non-singular matrices and the equations (6.19), (6.20), (6.21) are linear systems. Linear Least Square method can be applied to estimate the parameters. To obtain S and O, we simply use the $pinv$ function in Matlab which is used to calculate Moore-Penrose pseudo-inverse of matrixes, to identify the parameters.

6.3 Device and Experiment

The self-designed wireless Micro-IMU device that used for our research is shown in Figure (6.2).

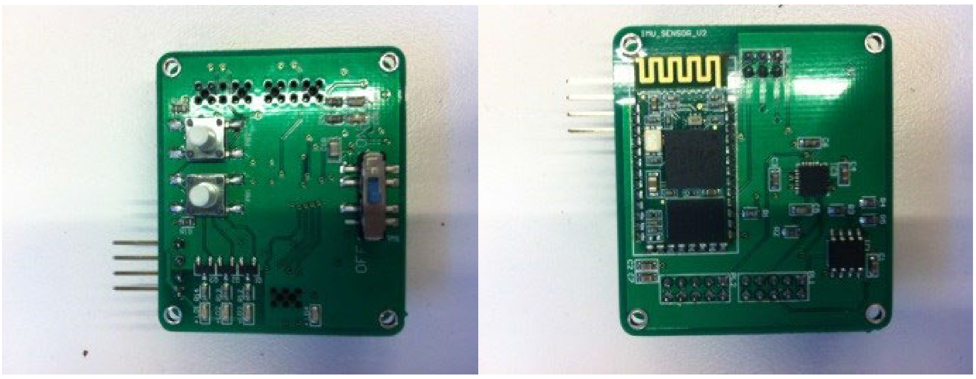


Figure 6.2: The top side (left) and bottom side (right) of IMU device

Lines through three SMD (Surface Mounted Devices) connectors between two boards build a reliable communication from MCU (Micro Control Unit) to periphery devices. On the top board that integrated MSP430F5528, a communication module named USCI (Universal Serial Communication Interface) module takes major responsibility for communicating with the bottom board. There are also several small modules, containing different communication protocols, integrated in USCI module [154]. In our designed code, three different protocols are used for three periphery devices. The relationship between MCU and periphery devices is illustrated in Figure 6.3.

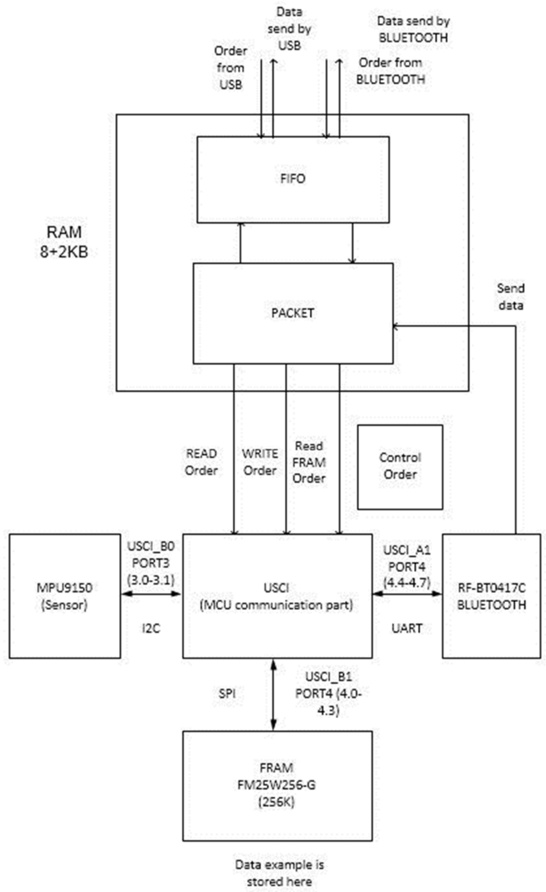


Figure 6.3: The Structure of the IMU

The first one, the USCI_B0 module supports I2C protocol [154] communicating with MPU9150. In this communication, USCI acts as the master while MPU9150 acts as the slave. Hence, USCI controls write or read through a bus. The bus consists of two lines that one is a serial data (SDA) line and another is a serial clock (SCL) line. Both of them are used to control and communicate. At the beginning of communication, I2C line needs a "start" mark to tell either the master or slave to start communications. The SDA line pulls voltage from High to Low while the SCL line maintains a High. After that, master sends a 7-bits address and a 1-bit write/read order on the SDA line. The slave which matches this address will send an acknowledging signal to the master and then receiving or transmitting of data begins. The master and the slave could also operate 8-bit data (1 byte) every time. After 8-bits data have been transferred, 1 bit Acknowledge signal is required. Finally, the communication will require a stop signal to indicate the end. The SDA line will pull up voltage from Low to High and the SCL line maintains a High. Figure 6.4 illustrates I2C protocol.

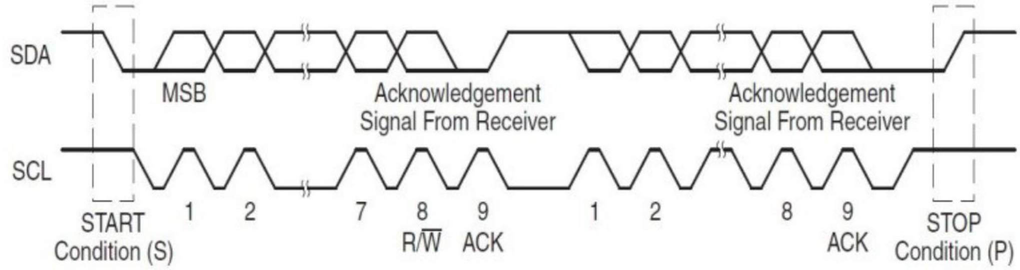


Figure 6.4: I2C Protocol

The second module is USCI_B1 which supports SPI mode [154]. This module is used to communicate with FRAM. The USCI_B1 module is the master and FRAM is the slave. The master provides clock signals for the slave. Thus, SPI applies synchronous communications. Data requiring transmission from the master first enters the Transmit Buffer and then moves to the Transmit Shift Register when this register is empty. After that, data reaches out to UCxSIMO and start transmitting from its MSB (Most Significant Bit). When the character is received, it first enters the Data Shift Register before moving to the SPI Receive Buffer. Also, the received data should pass through SOMI and reach the Receive Shift Register and finally move to the Receive Buffer. At this time, the receive interrupt flag UCRXIFG is set. The TX/RX operation is completed.

Figure 6.5 shows the SPI protocol.

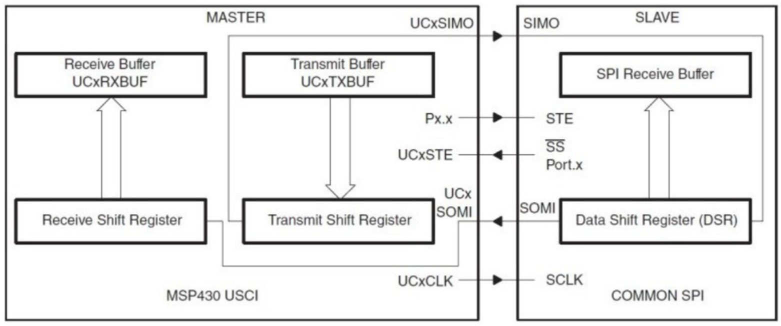


Figure 6.5: SPI Master Mode Protocol

The last module is USCI_A1 which supports UART (Universal Asynchronous Receiver/Transmitter) protocol [154]. UART communication is the only asynchronous communication in these three and its data format is illustrated in the figure on the bottom. The default voltage is high. When it falls down to a lower level, this means the “start” bit followed by an 8-bit data. After that an address bit, a parity bit and a stop bit are required. In total, one character consists of 14-bits. Figure 6.6 illustrates the protocol of UART communication.

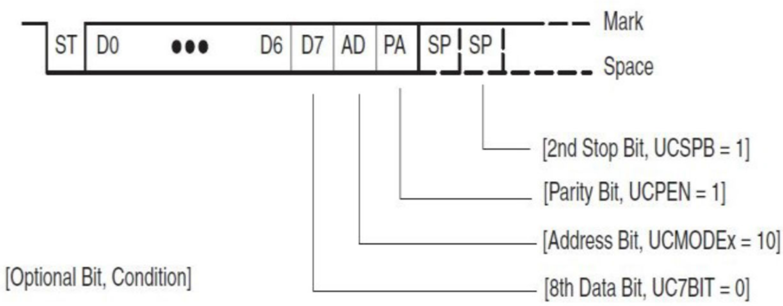


Figure 6.6: UART Protocol

The key part of this device is the sensor. MPU9150 integrates 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer. It uses 16-bits ADCs for accelerator and gyroscope output and 13-bits ADCs for magnetometer output. User programmable gyroscope full-scale range of ±250, ±500, ±1000, ±2000°/sec (dps) and the accelerometer with full-scale ranges of ±2*g*, ±4*g*, ±8*g*, ±16*g* and the magnetometer with full- scale ranges of ±1200μT could be selected in application [155]. Using 400 KHz I2C communicates with other devices. The features of MPU9150 that are used in our devices have been shown on table 6.1 [155].

Table 6.1: Features of MPU9150

Name	Type	Unit
Full Scale Range	±2	g
ADC Word Length	16	bits
Sensitivity Scale Factor	16,384	LSB/g
Sensitivity Changing vs. Tem	±0.02	%/
Nonlinearity	0.5	%
Noise Density	400	μg/√Hz

Finally, Bluetooth and USB (Universal Serial Bus) performs data transmissions from the IMU to the computer. The IMU transmits data through Bluetooth only under the condition that USB interface has not been connected to a computer. The type of Bluetooth that we integrated is RF- BT0417C and the speed of transmission is 9600 baud and protocol is 8N1 (8 data bits, no parity bit, 1 stop bit) which is similar with UART. If the USB was connected to a computer, the Bluetooth would not work. At this time, the USB is the major communication with computer. Our USB has been configured in high-speed mode which is 480Mbps.

Consequently, the IMU is constituted by 2 boards. The top board is the base board that integrated MCU and the bottom board integrates 3 periphery devices. Two boards communicate through USCI module with 3 different protocols. Communication between computer and IMU is relied on USB and Bluetooth.

In the experiment, we use a table lamp as a simple turntable as shown in Figure (6.7).

Figure 6.7: Experiment for Auto Calibration Method

Although the accuracy is low, the structure of the table lamp is quite similar with six degrees of freedom with a manipulator, which has 4 joints. Number 1 showed in Figure (6.7) can rotate around absolute Z axis. Number 2 and 3 are used to adjust the height of support. Number 4 can rotate around the joint. The micro-IMUs that were fixed on this device can reach to any position and posture and keep static. Number 5 is a plummet which is used to indicate the gravity direction. In auto-calibration method, our device should be set in N different random posture and record the accelerometer data received from the sensor. In the classical method, experiments require 6 orthogonal positions. That is, aligning one axis direction of accelerometer to local gravity each time. Due to this restricted requirement, the classical calibration method should apply high accuracy turntable. Unfortunately, such assistant equipment is not available in most university labs. Instead, we uses a paper roll constructed from an A4 sheet, as the IMU's support but still reaches an acceptable accuracy. Figure 6.8 shows details for the implementation of classical calibration experiment. The paper roll can just hold the edge of the IMU.

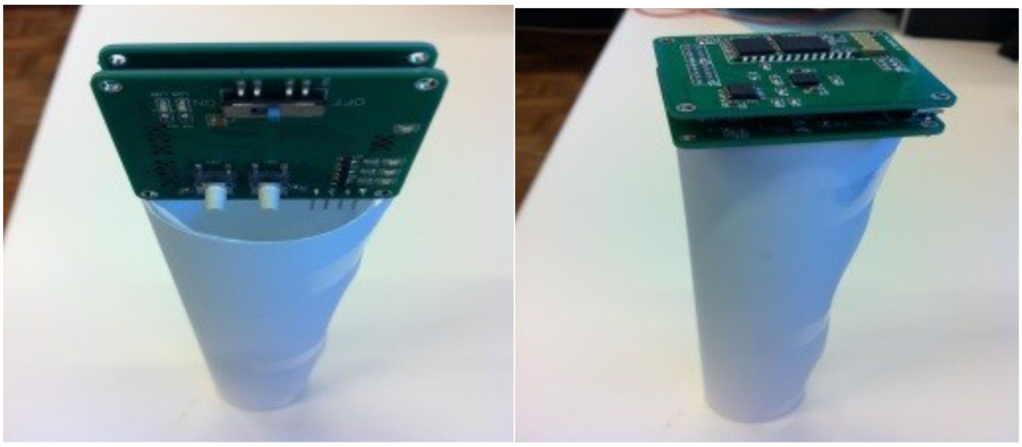


Figure 6.8: Experiment for Classical Calibration Method

This approximately orients the axis under calibration vertical to ground. After that, a plummet with a line could ensure the paper roll is parallel to the direction of gravity direction.

6.4 Results and Comparison

The results of the two methods are shown in Table 6.2:

Table 6.2: Results of Offset and Sensitivity

Parameter	Method A	Method B
S_x	0.6217E-04	0.6075E-04
S_y	0.6170E-04	0.6058E-04
S_z	0.6077E-04	0.6162E-04
O_x	0.0421	0.0374
O_y	-0.0148	-0.0144
O_z	-0.0748	-0.0729

The results showed above are offset and sensitivities which were calculated using Method A (Auto-calibration) and Method B (classical calibration). In order to test these two calibration results, we respectively printed these two sets of parameter values into the micro-IMU. New experiments, which execute 84 random postures, are performed for each set of model parameters respectively. We calculated the root of mean square value (RMS) of errors by equation (6.22) and compared these two methods by RMS. The results are listed in Table 6.3.

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \quad \ldots \qquad \text{Equation 6.22}$$

Table 6.3: Error RMS of Two Methods

	Method A	**Method B**
RMS	$0.074g^2$	$0.069g^2$

It was found that Method B has higher accuracy than Method A. We believe the major reason that degraded the performance of method A is coupling. For auto-calibration, every axis of the accelerometer affects each other in each observation. Specifically, in Method A, the experiment is based on N random positions and the accelerometer outputs. From equation (6.12), we can see in each position the errors of any accelerometer will influence the estimation results due to coupling effect. Method B, however, utilizes 6 orthogonal positions that have minimal coupling effect on each other. This is the main reason that Method B performs better than Method A. The second reason is that although 2 models use the same format of definition in acceleration, Method A's algorithm is much more complex than Method B's. A more complex algorithm requires more procedures for curve fitting. Hence, the error could increase during calculation.

However, the advantage of Method A is also obvious as it is attitude independent. That is, it is unnecessary to guarantee the orientation of 3 axes to accurately align with local gravity. As long as the device can be hold statically in a number of positions, calibration can be done successfully. On the other hand, Method B is simpler and also has higher accuracy than Method A but is attitude dependent. That is, if the required attitude with respect to local gravity is not guaranteed, Method B will generate extra calibration error.

6.5 Conclusion

This chapter investigates the modelling of the accelerometers of a self-designed micro-IMU. We compare two commonly used calibration approaches. The classical calibration method achieves relatively higher accuracy than the auto-calibration method. As a result, we recommend the classical calibration method; if the accurate turntable is available, the classical calibration method should always be the first choice. In future research, to implement online (in-field) calibration, we plan to develop efficient algorithms to simplify the calculation of parameters, which can be implemented in the embedded microprocessors with low computational capacity.

Chapter 7 : Cardiovascular Fitness Based on Interval Training Protocol

7.1 Overview

Heart rate is a very important physiological parameter that is corresponding to the exercise status. The Heart Rate (HR) is measured by the number of beats of the heart per minute. The experiments have been done on healthy but untrained subjects, and their physical attributes were provided in chapter five. The participants' data such as VO_2, HR, steps and direction were collected using $K4b^2$ and smartphone system and then processed using Matlab for system identification and modelling.

Exercising plays a vital role in improving and protecting the human being health; many diseases can be avoided by just exercising regularly, those diseases such as cancer, blood pressure, heart problems and diabetes. Heart Rate (HR) and Oxygen Uptake (VO_2) are key indicators of functional health status; their measurements can aid early detection of cardiac diseases [34, 156]. Cardiovascular fitness is defined as the ability of the heart and lungs to supply oxygen-rich blood to the working muscle tissues and the ability to use oxygen to produce energy for movement [157]. Cardiovascular fitness is measured as the amount of oxygen transported in the blood and pumped by the heart to the working muscles and as the efficiency of the muscles to use the oxygen. Regular exercise can increase cardiovascular fitness as the heart becomes more efficient at pumping oxygen-rich blood to working muscles and body tissues [38]. Increasing cardiovascular fitness means increasing the capability of the heart and the rest of the cardiovascular system in supplying oxygen and energy to the body.

The training protocol consists of three major phases; that is a warm-up, exercise and cools down. Warm-up prepares the body for more intense exercise by improving blood flow to the heart, increasing the muscle temperature and protecting against injury through improved flexibility of muscles [158]. The second phase in training protocol is the exercising; the main characteristics of this phase include the intensity, duration, frequency and mode of exercise [159]. Cooling down is the last phase of the training protocol and is defined as the phase that brings the body back to its normal physiological level after fast, vigorous exercise or activity by gradually slowing the pace of activity or by doing gentle exercises or stretches [160]. Any training or workout such as running, swimming or cycling that involves high intensity training session with resting periods is called interval training protocol. The interval training protocol has proven to build up and strengthen the athletes' cardiovascular system. It can usually be noticed that long distance runners are performing the interval training protocol as well as footballers. This newly developed, wearable exercise monitoring system has been customized to suit Interval Training.

The Portable Exercise Monitoring System was implemented by using the eZ430-Chronos watch [131] from Texas Instruments, BM-CS5 wireless chest strap [133] from BM Innovations and K4b^2 [124] from COSMED. The eZ430-Chronos watch is a flexible and powerful development tool, which can integrate heart rate monitor as one of the physiological sensors by using low power consumption wireless communications. The BM-CS5 is using BlueRobin^{TM} data transmission technology to measure and transmit the heart rate values wirelessly.

$K4b^2$ is the first portable system for pulmonary gas exchange measurement with true breath-by-breath analysis, $K4b^2$ has previously been reported to be valid, accurate and reliable [125, 126]. $K4b^2$ has been used in this study to compare the measured HR values with that one from eZ430- Chronos watch and it has been found that they are nearly identical under proper pre-signal processing, which means using the proposed portable exercise monitoring system is valid, reliable and cost-effective in building cardiovascular fitness.

7.2 Rehabilitation and Training Monitoring System

The Portable and Wearable Rehabilitation and Training Monitoring System (Figure 7.1) consists of two parts, the eZ430-Chronos watch and the BM-CS5 chest strap. However, $K4b^2$ has been used in this study to verify and compare the HR values. The interval training protocol has been adopted in this study to strengthening the cardiovascular fitness, in this protocol, the exerciser is required to shift between high intensity and low intensity exercise.

Figure 7.1: Rehabilitation and Training System

Calculating the safe training zone:

The Inbar [41] formula has been used to find out the HR_{max} for each participant as following:

$$HR_{max} = 205.8 - 0.685 \times age \qquad \text{Equation 7.1}$$

$$= 205.8 - 0.685 \times 26$$

$$= 187.99$$

$$\approx 188 \text{ bpm}$$

So, as we can see that for participant whose age is 26 years old, his HR_{max} is approx. 188 bpm. The subject must reach 80% of his HR_{max} to guarantee an improvement in the cardiovascular fitness [34].

The proposed system monitors and guides the exerciser through audio stimulation to alter between High Intensity (the subject reaches 80% of HR_{max}) and Low Intensity (subject reaches 60% of HR_{max}) exercises in order to build and strengthening his cardiovascular system fitness.

Volunteers:

Five volunteers with different ages and physical characteristics were participated in the experiments; all volunteers were free from any health issues. The subject's physical characters are shown in the table 7.1:

Table 7.1: Physical Characteristics of the Participants

Subjects	Age (Yrs)	Height (cm)	Weight(Kg)
1	25	168	73
2	27	174	75
3	30	177	72
4	33	168	74
5	26	172	65

As mentioned earlier, the subject must reach 80% of his HR_{max} to guarantee an improvement in the cardiovascular fitness, and based on equation (7.1), the HR_{max} have been calculated for all participants along with their High Intensity and Low Intensity HR values as shown in table 7.2:

Table 7.2: Participants HR_{max} Values

Subjects	Age (Yrs)	HR_{max}	60% of HR_{max}	80% of HR_{max}
1	25	189	113	151
2	27	187	112	150
3	30	185	111	148
4	33	183	110	147
5	26	188	113	150

Flowchart:

The flowchart of the proposed health monitoring system running on eZ430-Chronos watch is represented in Figure 7.2:

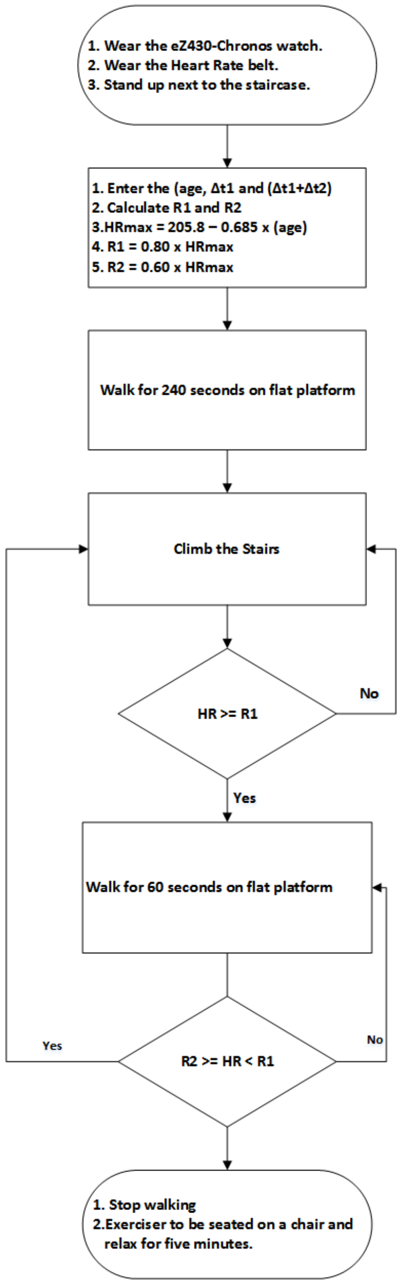


Figure 7.2: Rehabilitation and Training System Flowchart

In this instance, after a successful connection between the wearable eZ430-Chronos watch and the BM-CS5 chest strap, the system prompts the exerciser to enter his age and the recommended training zones are computed based on the HR values.

Experiments:

The proposed system guides the exerciser during any exercise whether indoor or outdoor through audio stimulation to switch between high and low intensity exercise to guarantee cardiovascular fitness increase and development.

The proposed system tested on stairs climbing exercise. The experiment starts by asking the subject to wear the eZ430-chronos watch on their hand, the BM-CS5 chest strap on their chest, and the $K4b^2$ system and mask. The devices will continually measure the HR and the subject is required to act accordingly.

In this experiment, the exercise starts by warming up phase which is walking on a flat platform for 240 seconds; the exercising phase starts by climbing the stairs for a specific time, i.e., 60 seconds, or until the subject reaches 80% of his HR_{max}. The system will produce an audio tone to notify the subject to alter the exercise intensity from High Intensity to Low Intensity exercise, which is in this case is walking aside on the step for either 60 seconds or until he reaches 60% of his HR_{max}, Once this condition becomes true, the system will produce a different audio tone to notify the subject to switch back to High Intensity exercise. High Intensity exercise is climbing the stairs, while walking on the same stair is considered Low Intensity exercise as shown in Figure 7.3.

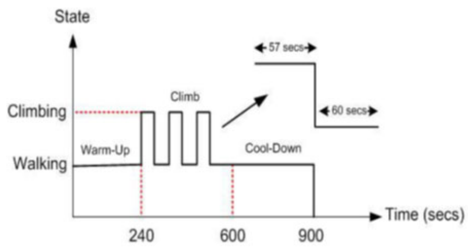


Figure 7.3: Walk-Climb-Walk Interval Training Protocol

The subjects has been seated and rested for five minutes after completing the final walk.

Figure 7.4 shows the HR and VO_2 experimental results for subject 5 under the proposed interval training protocol.

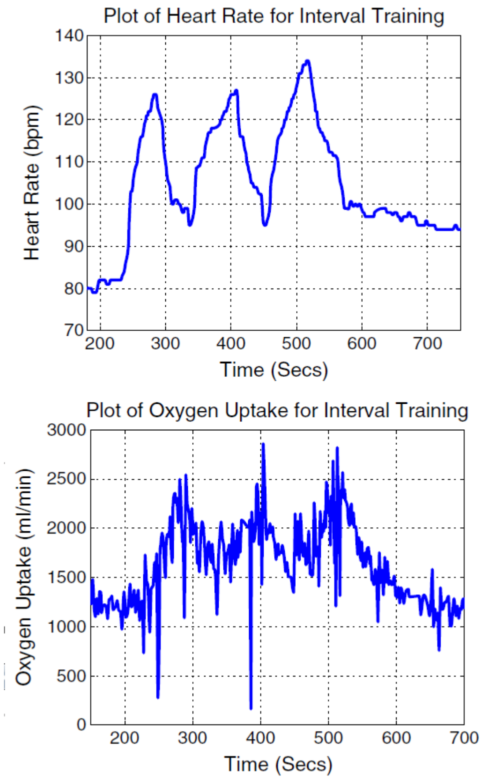


Figure 7.4: HR and VO2 Experimental Results - Subject 5 - ITP

Results:

The interval training protocol aim in the study is to develop the cardiovascular fitness system, having this in mind; the exerciser is required to train in a range of 70% to 80% of his HR_{max}, as mentioned earlier, climbing the stairs represent onset stage in the training protocol and walking on the same step is considered as offset period.

A controller with self-adaption feature that can tune the duty cycle Δt1 and the period (Δt1 +Δ t2) gives the exerciser the opportunity to reach his desired setpoints after a certain number of training sessions as shown in Figure 7.5

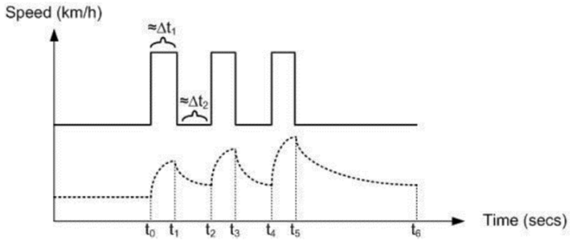


Figure 7.5: Controller Input/output and HR Response during ITP

Figure 7.6 shows the controller structure that has been implemented in the watch, where the exerciser needs to enter (age, Δ t1 and (Δt1+Δt2), and based on these values the R1 and R2 are calculated, where, R is the onset value and R2 is the offset value.

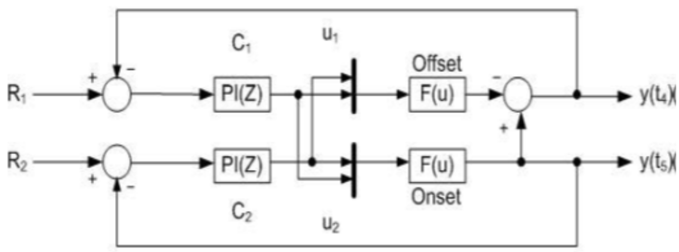


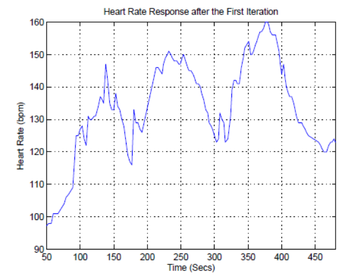
Figure 7.6: Controller Structure

The watch and its controller will guide the exerciser of how many iteration does he need to reach his setpoints, and the controller will tune up the outputs values until it reaches the desired setpoints. The watch and controller parameters are as shown in table 7.3:

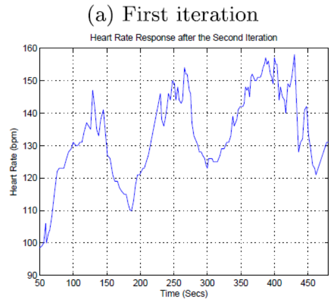
Table 7.3: Watch and Controller Parameters

Iteration	Onset Time	Offset Time	Period	Duty Cycle	$y_{(t4)}$	$y_{(t5)}$
Ref.	60	60	120	50	113	150

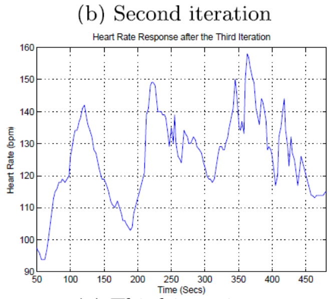
In the first iteration, 60 seconds is set to be the onset and offset times. At the end of the first training session, the reading of HR at t4 and t5 were observed and feed backed to the multi-loop control system to update the controller outputs inputs (the duty cycle and the period). Accordingly, the controller adjusts the time of onset and offset periods for the next training session. Figure 7.7 shows the heart rate response after the first, second and the third iterations.



(a) First iteration



(b) Second iteration



(c) Third iteration

Figure 7.7: HR Response - Stairs Climbing Exercise - Subject 5 - ITP

Table 7.5 shows the watch and the controller parameters after the third iteration:

Table 7.4: Watch and Parameters after the Third Iteration

Iteration	Onset Time	Offset Time	Period	Duty Cycle	$y_{(t4)}$	$y_{(t5)}$
Ref.	60	60	120	50	113	150
1	54.48	56.18	110.66	49.23	123	160
2	55.52	56.59	112.11	49.52	122	156
3	56.25	56.78	113.03	49.77	118	157

We can conclude from the previous table that the exerciser has almost reached to the desired setpoints after only 3 iterations. We kept in mind that after certain number of training sessions, the training capacity of the exerciser will improve, and this might affect the result of his HR response.

7.3 Conclusion

A prototype of a portable health monitoring system has been developed, implemented and tested. The proposed system allows continuous monitoring of heart rate during any exercise and guides exerciser using audio stimulation to increase or decrease exercise intensity in order to build and strengthening the cardiovascular system based on interval training protocol.

The developed Portable and Wearable Monitoring device and its associated algorithms are technically feasible in various exercise monitoring and regulation related projects. Based on this portable system, recently, a new effective interval training protocol has been proposed and implemented in the Centre of Health Technologies, University of Technology Sydney (UTS). Furthermore, the developed system can be utilized in the control of other automated exercise machines, such as treadmill or bicycle for the rehabilitation program and exercise training.

Chapter 8 : Modelling of Heart Rate Responses during Stairs Climbing Exercise

8.1 Overview

Heart rate is a very important physiological parameter that is corresponding to the exercise status. The Heart Rate (HR) is measured by the number of beats of the heart per minute. The experiments have been done on healthy but untrained subjects, and their physical attributes were provided in chapter five. The participants' data such as VO_2, HR, steps and direction were collected using $K4b^2$ and smartphone system and then processed using Matlab for system identification and modelling.

8.2 Climbing Stairs Protocol

The exercise protocol of the Stairs climbing exercise requires the participants to climb the stairs until he reaches 80% of his HR_{max} and switch to low intensity exercise until he reaches 60% of his HR_{max}.

The intensity of the climbing stairs exercise were setup between 60% and 80% of the HR_{max} for two reasons, the first is that this is the recommended exercise intensity for unfit but healthy people and for people with cardiac problems [1]. The second reason is to keep the linearity relationship between HR and VO_2 as the relationship between HR and VO_2 becomes non-linear during light and very highly intense activity [156]. It is very important to maintain the HR and VO_2 values within the linear part, the above settings were chosen and the participant were required to perform 80% of his maximum heart rate that is recorded as onset exercise level and then the offset exercise level is when he reaches 60% of his maximum heart rate.

As mentioned before, each subject completed four rounds of exercise that starts by warming up phase for three minutes by walking slowly on the steps. Then exercise phase starts and it requires the participant to climb the stairs until he reaches 80% of his maximum heart rate and then descend the stairs until he reaches 60% of his maximum heart rate. The last phase is the recovery phase that lasts for five minutes to avoid any kind of stiffness. Figure 8.1 below shows the experimental training protocol.

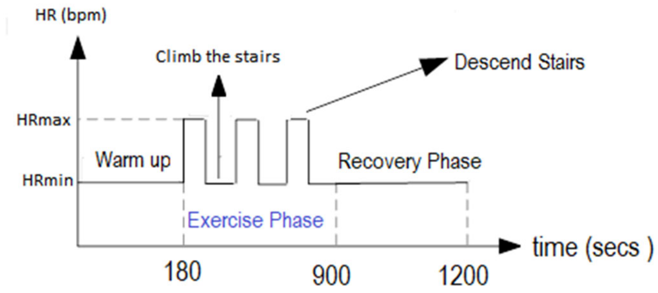


Figure 8.1: Stairs Climbing Exercise Protocol

8.3 Heart Rate and Oxygen Consumption Profiles

The participants' data were collected using K4b^2 device to collect the VO_2 and VCO_2 breath by breath and the developed smartphone system to measure the participants' heart rate beat by beat and direct the user through voice commands and audio stimulation to follow the exercise protocol. Figure 8.2 shows the original HR signals of the participants while following the exercise protocol, while Figure 8.3 shows their VO_2 at the same time.

Many approaches such as least square and maximum likelihood could apply to linear system identification to find out the HR response to exercise extensity; however, the accuracy of system identification results were not satisfactory.

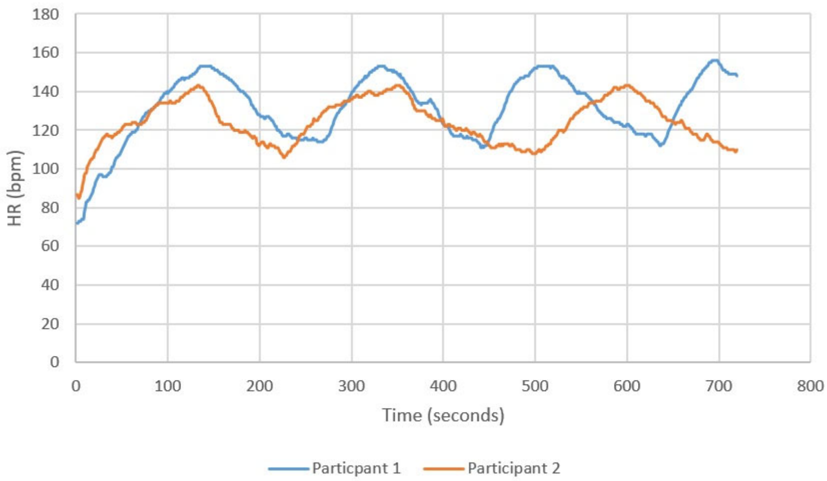


Figure 8.2: Participants HR Profile - Stairs Exercise

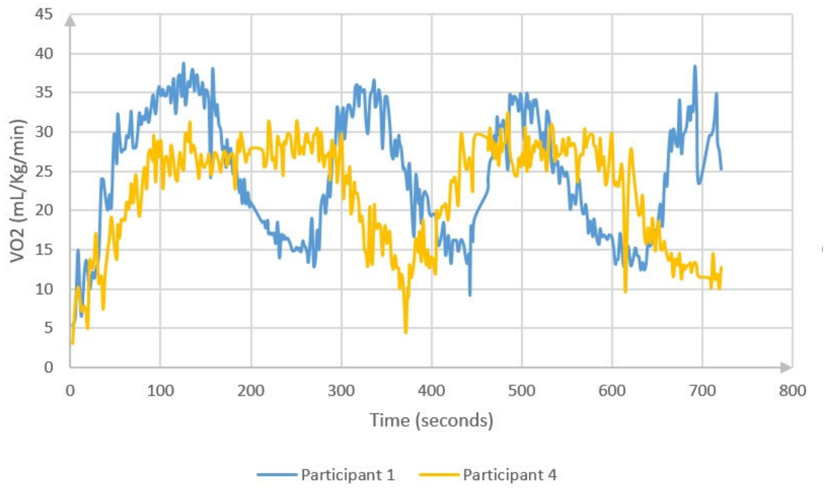


Figure 8.3: Participants' VO_2 Profile - Stairs Exercise

8.4 Non-parametric Dynamical Modelling of Finite Impulse Response based on Kernel:

8.4.1 Overview

Sports physiology is a field about studying the changes of human structure and function under the influence of sports activity and training. Among the broad range of physiological indexes studied in sport physiology, heart rate (HR) is one of the most frequently used. HR is measured by the number of contractions (beats) of the heart per minute (bpm). The American Heart Association states that the HR of a normal resting adult human is from 60 to 100 bpm. The maximum heart rate (HR_{max}) is the highest HR that an individual can achieve without severe problems through exercise stress [161].

Human HR changes with exercise status, such as exercise load or exercise speed, and this variation can be considered as a linear system. Some classical methods such as least square, maximum likelihood, and prediction error methods could apply to linear system identification about HR signal responses to the exercise status. However, the accuracy of identification results using these traditional methods is not satisfactory due to the insufficient stimulation [9, 10, 11]. When the prior information is not enough to determine the structure of the system, the non-parametric modelling method is a better choice [12, 13]. This method has been applied with the kernel-based regularization approach [14, 15, 16] by several researchers. The non-parametric method achieves a high accuracy and robustness in system identification when studying the dynamics of HR response to exercise status with a well-designed kernel strategy and regularization term.

Energy consumption, heart rate, and minute ventilation volume will increase until reaching a peak while going upstairs (ascending). These physiological data will decrease when going downstairs (descending) [17]. The step response of HR are approximated as a first-order system in several studies [18, 19, 20, 21]. However, the HR changing in these studies often reach a steady platform that corresponds to the same trend as the step response. In this case, the dynamic relationship between the exercise status and HR is uncertain.

8.4.2 First Order System and Step Response Input

According to [8, 162] the heart rate responses to exercise can be approximated as a first order system that has only one pole as shown in figure 8.4:

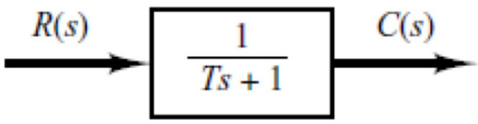


Figure 8.4: Block Diagram of First Order System

The first order system is defined as a system whose input and output relationship is a first order differential equation. The order of the differential equation is the order of the highest order derivative present in the equation and is given in the following equation [163]:

$$\frac{dy}{dt} + p(t)\,.\,y = q(t) \quad \ldots \qquad \text{Equation 8.1}$$

The solution to equation 8.1 is given by equation 8.2 as following:

$$y = \frac{\int u(t)\,.\,q(t)dt + C}{u(t)} \quad \ldots \qquad \text{Equation 8.2}$$

Where:

$$y = e^{\int p(t)dt} \quad \ldots \qquad \text{Equation 8.3}$$

Another method to solve linear differential equation is to apply the Laplace transform on our system which is considered as Linear Time Invariant (LTI) system. The frequency domain gives a better and easier understanding of the system characteristics when compared to the time domain approach. The Laplace transformation of equation 8.1 can be given as:

$$Y(s) = \frac{k}{\tau s + 1} \quad \ldots \qquad \text{Equation 8.4}$$

The key parameters that determine the system behavior are:

- K= DC gain
- T = time constant

The time constant characterizes the speed of response of a first-order process, it is a measure of the time necessary for a process to adjust to a change in the input, while the static gain characterizes the sensitivity of the output to the input signal [164].

The raw data of heart rate and the stairs exercise direction are shown in Figure 8.5, which indicates the step response of HR regarding the stairs exercise. The nonparametric estimation method based on kernel technique will be used to build the HR model for stairs exercise.

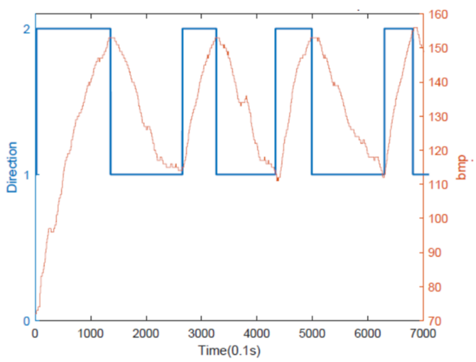


Figure 8.5: Measured HR and Exercise Direction of One Participant

The exercise status which varies between ascending and descending is often considered as a step response input, and the HR is the output of the system. Thus, a single input single output (SISO) system is used to describe the response when the output is considered as a discrete case in equation (8.5):

$$y(t) = \sum_{\mathrm{T}=0}^{\infty} u(t - \mathrm{T}) g[\mathrm{T}] + \epsilon(t), \; t = 1,2,\dots,N, \; \dots \qquad \text{Equation 8.5}$$

where u(t) is the input, y(t) is the output, g(τ) is the impulse response, t is the sampling time, ε(t) is Gaussian white noise, and N is the total number of sampling. All the elements (row) in y(t), u(t−τ) and ε(t) of equation (8.5) are stacked to matrices form Y , φ and ε. g(τ) = θ ∈ Rm is defined, where the vector θ ∈ Rm contains the Finite Impulse Response (FIR) coefficients. Then the equation (8.5) is rewritten as a matrix form:

$$\boldsymbol{Y} = \emptyset\boldsymbol{\theta} + \boldsymbol{\varepsilon}. \dots \qquad \text{Equation 8.6}$$

The estimation of $\boldsymbol{\theta}$ can be solved by LS estimation as [4]:

$$\widehat{\theta} = arg \min_{\theta \in R^m} (\|\mathrm{Y} - \emptyset\theta\|^2 \quad \dots \qquad \text{Equation 8.7}$$

A regularization term is added to equation (8.7) in order to regularize the estimation and guarantee the effectiveness of the obtained model [16]. JR($\boldsymbol{\theta}$), which belongs to a Reproducing Kernel Hilbert Space (RKHS), H is defined as the regularization term:

$$J_{\mathcal{R}}(\theta) = \theta^{\mathrm{T}} \mathrm{K}^{-1} \theta \qquad \dots \qquad \text{Equation 8.8}$$

where $\boldsymbol{K}$ is a suitable kernel matrix. Then the estimation of $\boldsymbol{\theta}$ is:

$$\widehat{\theta} = arg \min_{\theta \in R^m} \left(\|\mathrm{Y} - \emptyset\theta\|^2 + \gamma\, \theta^{\mathrm{T}}\, \mathrm{K}^{-1}\, \theta \right) \qquad \dots \qquad \text{Equation 8.9}$$

Where γ is a positive scalar.

After adapting, the equation (8.9) could be described as:

$$\widehat{\theta} = \left(\mathrm{K}\,\phi^{\mathrm{T}} + \gamma\,\mathrm{I}_m\right)^{-1} \mathrm{K}\,\phi^{\mathrm{T}}\,\mathrm{Y} \quad \ldots \qquad \text{Equation 8.10}$$

Where $I^m \in R^{m\times m}$ is an identity matrix with the dimension of $m \times m$.

In the kernel respect, Stable Spline (SS) kernel is chosen from various kernel [165] [166]. The SS kernel is described as following:

$$\mathrm{K}(i,j) = \frac{c}{2}\ e^{-\beta min(i,j)} - \frac{c}{6}\ e^{-3\beta max(i,j)} \qquad \ldots \qquad \text{Equation 8.11}$$

Where $c \geq 0, 0 \leq \beta < 1$.

The parameter of γ, c and β in this identification method need to be well-selected. The tuning is based on previous research [16, 167] and the optimal combination of the parameters is selected. The principle of tuning is to find the best fitness between the real HR and estimated HR under the premise of ensuring a smooth IR. Thus, the following specifications are chosen after tuning: γ = 200, c = 1 and β = 0.996

8.5 System Identification:

8.5.1 Overview

System identification is a discipline that originated in control engineering; it deals with the construction of mathematical models of dynamic systems using measurements of their inputs and outputs. In control engineering, system identification is used to build a model of the process to be controlled; the process model is then used to construct a controller.

In biomedical engineering, the goal is more often to construct a model that is detailed enough to provide insight into how the system operates.

8.5.2 Data Filtering and Preparation:

The System Identification toolbox from Matlab software has been used in this study to obtain and establish the system first order process model. In order to obtain the desired model from our experimental data, the raw data has been interpolated, averaged and filtered to be fitted in the system identification toolbox. The interpolation is a method of constructing new data within the range of a discrete set of known data points. In engineering, interpolation is the ability to estimate the values of a function obtained by sampling or experimentation for a limited number of values of the independent variable [168].

Interpolation can be simply defined as an estimation of a value within two known values in a sequence of values. There are many different interpolation methods such as linear interpolation, polynomial interpolation and spline interpolation.

The VO_2 and VCO_2 values which were collected using the Cosmed K4b^2 as we have explained earlier in Chapter 5 don't have a fixed sampling rate as the data had been recorded breath by breath and it's not possible by any mean to record the breathing based on fixed rate or timing.

The $\boldsymbol{interp(x, r)}$ function from Matlab is utilized in order to apply interpolation on the collected raw VO_2 and VCO_2 data by resampling the data at a higher rate using low pass interpolation.

A sample of the collected raw VO_2 and VCO_2 using the $K4b^2$ are listed in table 8.1 and it is obvious that there is gaps in recorded values, so that the interpolation process is very important at this stage for the system identification process.

Table 8.1: Raw Collected (VO_2 & VCO_2) before Interpolation

Time (Seconds)	VO_2/Kg (ml/min/Kg)	VCO_2 (ml/min)
1	4.905123422	290.0542089
2	5.409004216	5.409004216
5	6.31762075	6.31762075
8	14.94550502	14.94550502
10	9.822928266	9.822928266
12	6.60166538	6.60166538
15	12.05436566	12.05436566

The code behind the interpolation process in Matlab is shown in Figure 8.6:

```

for x=1:m

    vo2_interp(x) = interp1(time,vo2,x);
    vco2_interp(x) = interp1(time,vco2,x);

end

    vo2_after_interp = vo2_interp(:);
    vco2_after_interp = vco2_interp(:);
```

Figure 8.6: Interpolation - Matlab

After running the Matlab code on our collected data, and setting the sampling at one second, Table 8.2 will become after the interpolation:

Table 8.2: Table 8.2: Raw Collected (VO_2 & VCO_2) After Interpolation

Time (Seconds)	VO_2/Kg (ml/min/Kg)	VCO_2 (ml/min)
1	4.905123422	290.0542089
2	6.01474857179415	331.062973535055
3	5.71187639385659	355.446077902362
4	5.40900421591903	379.829182269669

5	6.31762074973172	404.212286636976
6	9.19358217362416	628.354296760550
7	12.0695435975166	852.496306884124
8	14.94550502	1076.63831700770
9	12.3842166437010	881.680440328623
10	9.82292826599286	686.722563649549
11	8.21229682316990	567.769951984433
12	6.60166538034694	448.817340319318
13	8.41923214163668	573.577071375038
14	10.2367989029264	698.336802430757
15	12.0543656642161	823.096533486476

Another important Matlab signal-processing function was applied on the raw data is the $\boldsymbol{medfilt1}$ which has the syntax as shown in equation (8.12):

$$y = medfilt1(x, n) \quad \text{….. Equation 8.12}$$

We have applied the median filter on our raw VO_2 and VCO_2, the figures below show the raw sample data of VO_2 before and after applying the filter.

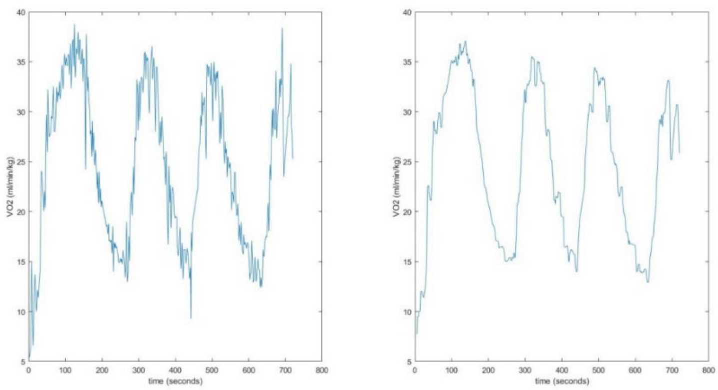


Figure 8.7: Measured VO_2 and Exercise Direction of One Participant

8.5.3 System Identification results and models:

Various reasons can lead to the changes of exercise status (load or speed) for different participants. The period number (A whole period is from the beginning of ascending to the end of descending.) and length of each period are also different. Thus, the study also focus on how the period number affects the identification results by comparing the fitness of HR estimation when the number of the period is 0.5, 1, 2. This estimation is conducted by the non-parametric model method. After the identification, the Rank Sum Test is added to illustrate the significant differences of the IR results.

The fitness rate of estimated output is calculated by the fit ratio NRMSE (normalised root mean square error):

$$Fit\ Ratio\ = \left(1\ -\ \frac{||\hat{Y}_N - Y_N||}{||Y_N - mean(Y_N)||}\right) \ldots \text{ Equation 8.13}$$

The representative non-parametric identification results with each period number are shown in Figure 8.8, which contains the impulse response and the estimated output (HR).

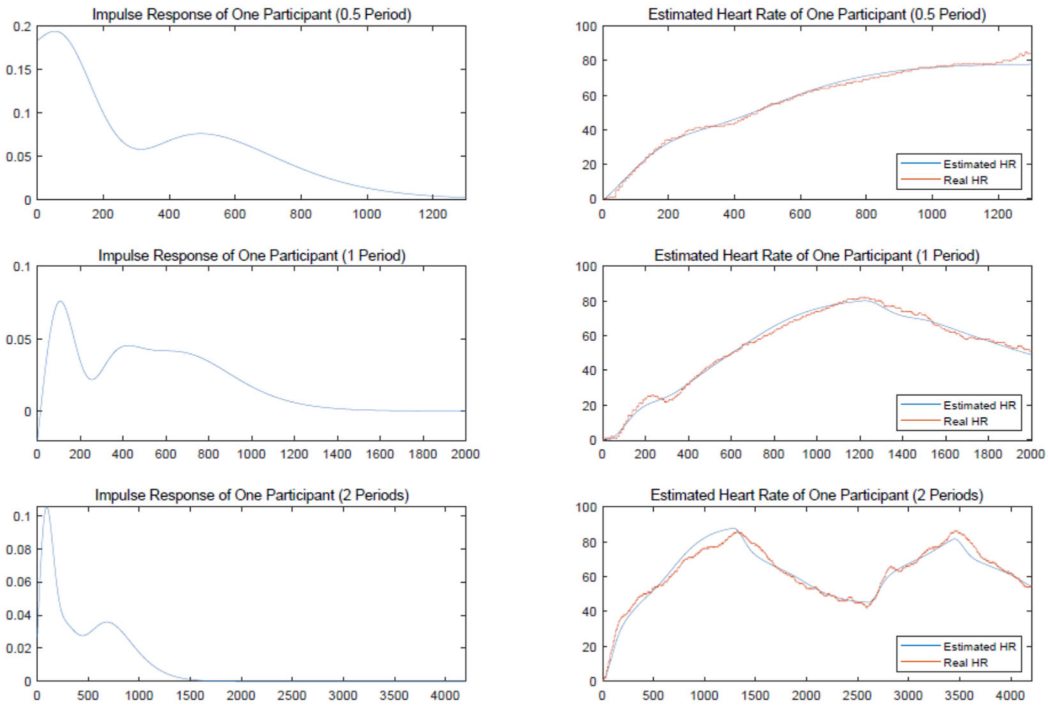


Figure 8.8: Impulse Response and Estimated HR of Three participants’

The boxplot to describe the fitness results of different period numbers is presented in Figure 8.9

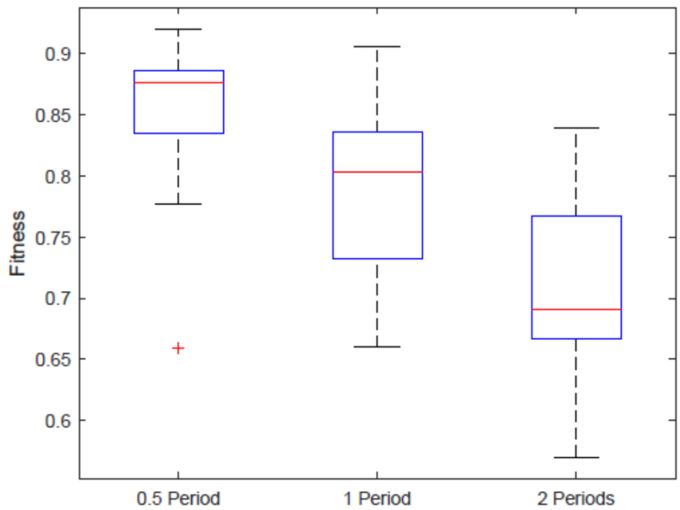


Figure 8.9: Fitness of Estimated Output of Different Period Number

The estimated output fitness of 15 participants are calculated using different methods, including non-parametric model, first-order, second-order and third-order transfer function model. The variance of fitness between these models are shown in (Figure 8.10). The variance of the fitness by different methods illustrate the stability of the model, which is shown in Table 8.2. The non-parametric model offers the smallest variance in both one period and two periods, which further proves that this type of modelling is more stable and suitable in this application. In addition, the first, second and third order systems show different performance with the changing of the period numbers which will be explained in results.

Table 8.3: The Variance of Fitness by Different Model Method

Model Type	One Period	Two Periods
First-order	0.0078	0.0086
Second-order	0.0882	0.0054
Third-order	0.0513	0.1713
Non-parametric	0.0051	0.0053

In order to demonstrate the significant difference between the different number of periods, we applied the Rank Sum Test on IR are used. Various period numbers are included as the data does not follow a normal distribution. Generally, $P < 0.05$ was considered as statistically significant. All the P value of the results means $h = 1$, which also means all the distinction of IR from different number of periods with same participants is significant.

8.5.4 Results and discussion:

The system identification results is explained in the following points:

1. The fitness of estimated output using non-parametric model is affected by the period number. In Figure (8.9), we could see that when we estimate the HR using half period data, the result is better than one period. With two periods data to estimate the HR, the fitness becomes lower than one period. However, the impulse response of half period has not reached the platform of zero, which means that half period input is not enough for system stimulation as in Figure (8.8). Thus, the one period is the better choice.

2. In Figures (8.10, 8.10), the best fitness result of each participant does not come from the same method. For some participant, their fitness results with both one and two periods using transfer function model appear to be below 40%. In some extreme cases, the value turns into negative. These results illustrate that the exercise-HR system is not a fix order system. Table (8.3) shows that the nonparametric and first-order model are more stable.

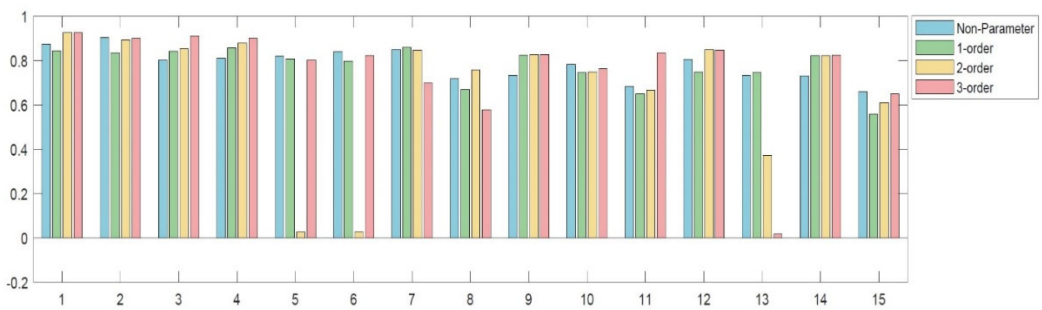


Figure 8.10: Fitness of Different Model of 15 Participant with 1 Period

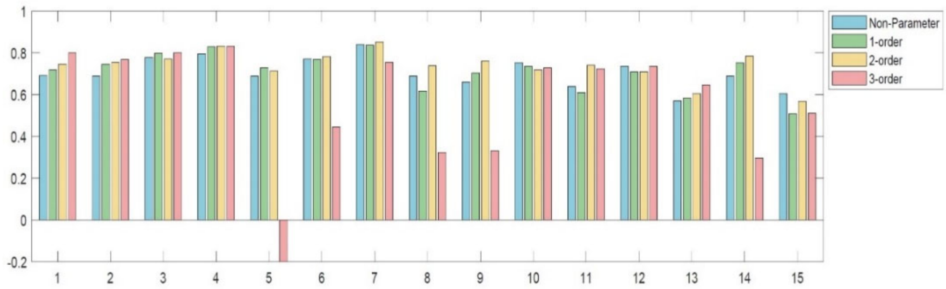


Figure 8.11: Fitness of Different Model of 15 Participant with 2 Period

3. One of the reasons for using the non-parametric method is to eliminate the influence of the system structure, which is explained above. The change of impulse response in non-parametric model is more flexible compared to the transfer function model. Thus, subtle trend changes of the HR could be estimated. Table 8.3 and Figures (8.10, 8.10), represent that using transfer function model, the first-order model receives a better performance in one period and the second-order model is suitable in two periods. This is due to the insufficient information in one period. Moreover, this finding also demonstrate the strength of the non-parametric model that the model is not affected by the amount of information provided from the number of periods.

8.6 Conclusion

In this chapter, the non-parametric model applied to investigate the dynamics of the HR response to stairs exercise status. The self-designed application provides a reliable technique to record HR data and to present safe and understandable exercise instructions. The protocol of the experiment guarantees a continuously changing HR. The SS kernel, regularization term, and appropriate parameter are applied in the non- parametric model. The identification result of different period numbers are compared, and the transfer function model, which includes three types of system order, also implemented for comparison purpose. The impulse response from the non- parametric model is more flexible, which ensures that the slight changes in HR can be estimated. For each participant, the best fitness of estimated HR is obtained through different order of transfer function models. Therefore, the stability differences between these two models (transfer function model and nonparametric model) show that the non-parametric model is preferable in stair exercise status identification.

Chapter 9 : Conclusion and Future Work

9.1 Conclusion

Exercising plays a vital role in improving human being health; exercising regularly can protect from many diseases and improves overall body health. Cardiovascular fitness is an indication of health status. It reflects the capacity of the respiratory system to carry out the exercise, and it describes the ability of the heart, lungs a well as organs to deliver and consume oxygen during physical activity. Oxygen consumption (VO_2) and heart rate (HR) are key indicators within the cardiovascular system; their measurement can help in improving the cardiovascular fitness system.

HR is measured using the wearable heart rate sensor, While, the oxygen consumption is measured using the $K4b^2$ device. The $K4b^2$ is a portable device measure breath-by-breath VO_2. $K4b^2$ is a versatile system and was used because it has previously been reported to be valid, accurate and reliable. It can be used in the field or in the lab without any kind of limitation. It has been used during all the experiments in the field to measure the VO_2 and VCO_2.

To obtain the accurate measurements of VO_2 and VCO_2 using the $K4b^2$ device, three types of analyzer calibration have to be performed before data measurement and collection process. Room air calibration, reference gas calibration and delay calibration. These calibrations are essential to update the baseline and the gain of the analyzer in order to match the readings with the predicted reference gas and atmospheric values.

The relationship between the HR and VO_2 are linearly related during moderate exercises, which means that both VO_2 and HR increase linearly with increasing exercise intensity up to near-maximal exercise. However, the relationship between HR and VO_2 becomes non-linear during light and very highly intense activity.

The physiological response of the exercise depends on the intensity, duration and frequency of the exercise as well as the environmental conditions. During any physical exercise, the demands of oxygen are increased in the individual's body. This changes the functioning of cardiovascular and respiratory systems, which causes dynamical variations in the various physiological variables such as heart rate (HR) and oxygen consumption (VO_2).

Using the built-in sensors such as accelerometer, gyroscope and barometer, we have proposed a movement algorithm to detect the participants' movement during walking, running or climbing stairs. Also, the algorithm detects the walking or running pace and through voice commands can direct the user to either increase or decrease his pace. The direction of the participant can also be detected, whether walking forward, backward, upstairs or downstairs. The developed algorithm has been implemented for safe, and effective exercise and rehabilitation under free-living conditions are not well researched.

In addition, the modelling of the accelerometers of the self-designed micro-IMU was investigated. We compare two commonly used calibration approaches. The classical calibration method achieves relatively higher accuracy than the auto-calibration method. As a result, we recommend the classical calibration method; if the accurate turntable is available, the classical calibration method should always be the first choice. In future research, to implement online (in-field) calibration, we plan to develop efficient algorithms to simplify the calculation of parameters, which can be implemented in the embedded microprocessors with low computational capacity.

Many volunteers have participated in the experiments, which have been carried out in indoor and outdoor environments. Each participant was required to wear the $K4b^2$ device, iPhone, eZ430-Chronos watch and heart rate sensors. The data was collected and then transferred to the laptop for modelling purpose.

Matlab system identification toolbox was used to establish the first, second and third order process model for each step response data. This study applies the non-parametric model to investigate the dynamics of HR response to stairs exercise status. The self-designed application provides a reliable technique to record the HR data and to present safe and understandable exercise instructions. The protocol of the experiment guarantees a continuously changing HR. The SS kernel, regularization term, and appropriate parameter are applied in the non- parametric model. The identification result of different period numbers are compared, and the transfer function model, which includes three types of system order, also implemented for comparison purpose. The impulse response from the non- parametric model is more flexible, which ensures that the slight changes of HR can be estimated. For each participant, the best fitness of estimated HR is obtained through different order of transfer function models. Therefore, the stability differences between these two models (transfer function model and non-parametric model) show that the non-parametric model is preferable in stair exercise status identification.

Two reliable and valid wearable exercise monitoring systems by using TI e Z430-Chronos watch as well as iPhone App, which can control the exercise intensity through audio stimulations and voice command to improve cardiovascular fitness of various exercisers.

Another area of this research is the implementation of the training and rehabilitation control system based on the developed nonparametric model. The control system was implemented as an application on Apple iPhone targeting athletes and untrained people.

In addition, the control system was also implemented on a wearable and cheap TI eZ430 Chronos watch that can be easily operated by patients or older people. This research is implemented in a real-life situation, and it showed promising results.

A prototype of portable health monitoring system has been developed, implemented and tested. The proposed system allows continuous monitoring of heart rate during any exercise and guides exerciser using audio stimulation to increase or decrease exercise intensity in order to build and strengthening the cardiovascular system based on interval training protocol.

The developed Portable and Wearable Monitoring device and its associated algorithms are technically feasible in various exercise monitoring and regulation related projects. Based on this portable system, recently, a new effective interval training protocol has been proposed and implemented in the Centre of Health Technologies, University of Technology Sydney (UTS). Furthermore, the developed system can be utilized in the control of other automated exercise machines, such as a treadmill or bicycle for the rehabilitation program and exercise training.

9.2 Future Work

There are some problems that remain open to future research. Although the approach to the modelling and control of human cardiovascular responses to exercise has been established for treadmill and stairs exercises, more various exercises such as swimming and jogging need to be included and build a universal nonparametric modelling that can accommodate all these exercises.

The exercise and rehabilitation system requires further development to improve its performance, reliability and ability to handle wide age range diversity. It is intended that the system will be redesigned to fulfill different age requirements. The designed training system itself requires additional adjustment to handle more physical targets such as fat burning, developing endurance and aerobic capacity and developing the lactic acid system. More experiments on male and female subjects will be conducted to validate the results that we have reached in this study.

Further common environments will be investigated, such as free speed running, swimming and jumping. These types of environments can have a wide range of effects on the individual or exerciser. Therefore, the ability for the designed controller and the interval training to control and cope respectively with these training schemes under free-conditions environments would be beneficial. The controller design will be improved to quickly and effectively reach the desired setpoints. All efforts will move forward towards minimizing the number of iterations for each exerciser.

Furthermore, the controller requires some improvement, and we will aim for a new controller design which can adjust more than two inputs to regulate the values of each single interval within the interval training protocol not only to regulate the lowest and the highest point of the last period of HR response. The new design has to give the exerciser the freedom to choose which response he or she needs to regulate HR or VO_2. The new design also needs to take into account the intermission between the interval training sessions and the difference in the physiological conditions for each exerciser before and after each training session.

Another important issue in the outdoor exercise monitor of human cardiovascular responses is the reliability of the wireless network involving smartphone applications and a set of portable and non-invasive sensors. The future studies will concern the multisensor signal processing such as ECG, respiration rate, body temperature, and signals from a GPS device and micro-IMU device.

The developed rehabilitation control system guides the patients through audio stimulation to control their heart rate as per the cardiologist recommendations (Varies from patient to patient). The next generation of this system will be able to connect to iCloud, which will enable the cardiologist to review their patients' recovery progress.

Another important issue to consider when implementing the rehabilitation control system is the accelerometer accuracy and its feasibility to use as a medical aid device.

Appendix A: Smartphone Code

The following code is written in SWIFT 3 using Xcode 8 on MacBook Air machine:

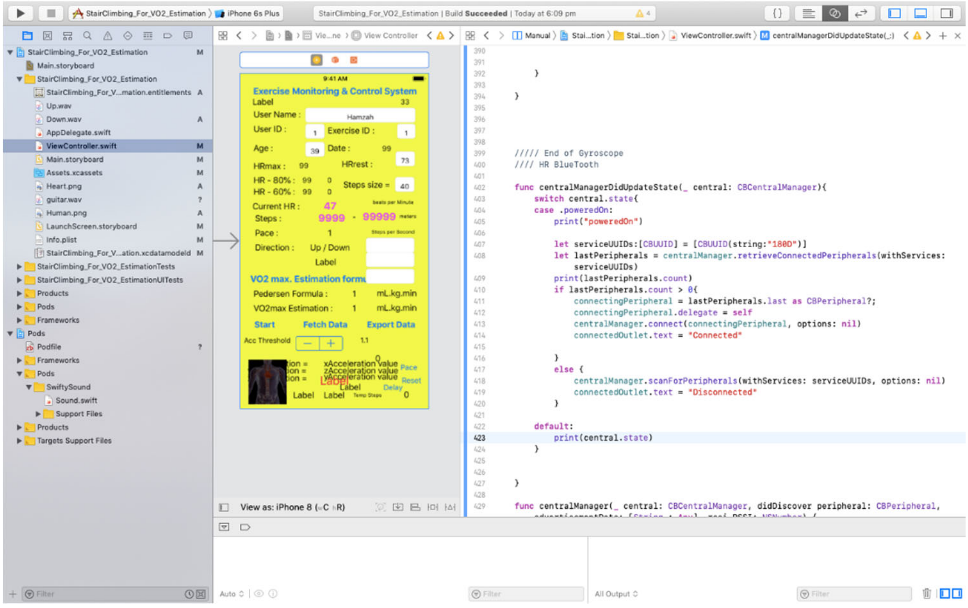


Figure A.1: SWIFT code Part I

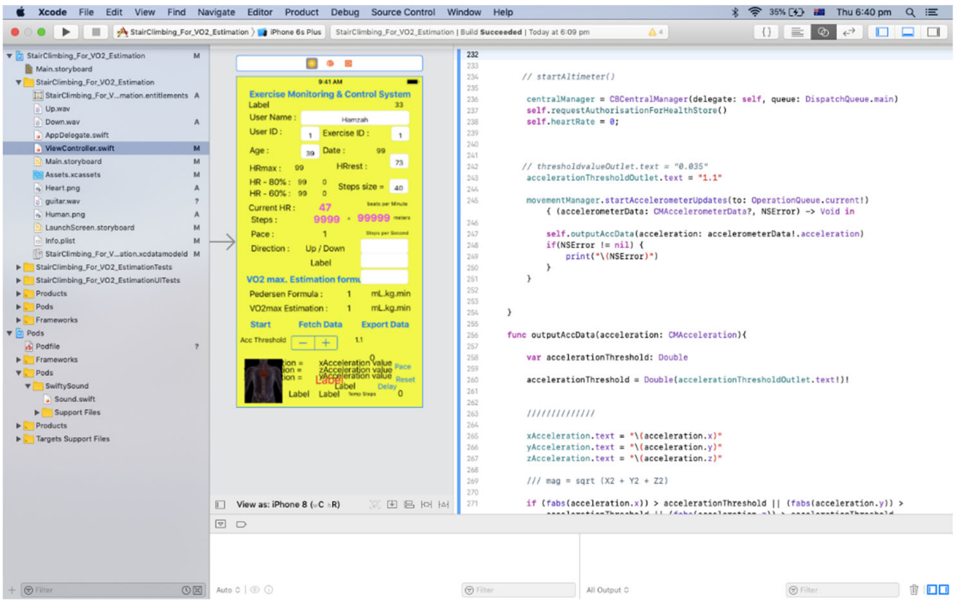


Figure A.2: SWIFT Code Part II

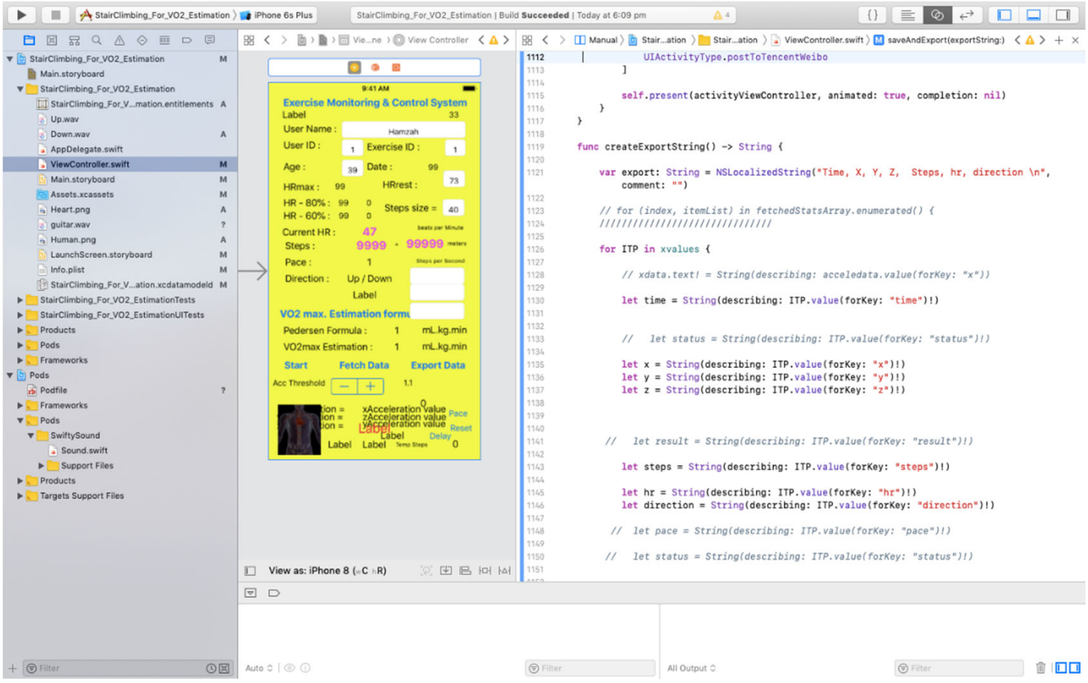


Figure A.3: SWIFT Code Part III

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