A Wearable Smart Sensing System

for Early - Fall Detection

MECH5845M Professional Project
A Wearable Smart Sensing System for Early - Fall Detection
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UNIVERSITY OF LEEDS

SCHOOL OF MECHANICAL ENGINEERING

TITLE OF PROJECT

A Wearable Smart Sensing System for Early - Fall Detection

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This project report presents my own work and does not contain any unacknowledged work from any other sources.

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Abstract

Falling is a very common cause of injury and may lead to irreversible damage to the elderly or patients. Compared with timely rescue after the fall, fall prevention is a more ideal solution. This study presents a wearable smart sensing system for early-fall detection. The system can detect and classify fall forward, fall backward and walk through six sensing units based on IMU sensors and SVM classifiers and a central control based on PC. The sensing units are powered by 5V miniature lithium batteries and cooperate with the central control through BLE. A weight matrix has been designed in central control for analysis of activities detection reports from the six units. The system development process, especially the development of parameters has been presented. The system has been validated by experiments of 20 fall forward, 20 fall backward and 20 walks performed by one participant. The experiments have proved that the proposed system can detect fall forward and fall backward within 500ms after fall start with success rates of 90% and 85% respectively. The average times spent for detection of fall forward and fall backward were 450 ms and 485 ms respectively. The accuracy of fall detection and walk detection has reached 100%. The results have proved that the early-fall detection system designed is an effective system with high accuracy, quick response for early-fall detection and a reasonable success rate of early-fall detection and classification.

Key words: Early-fall detection and classification; SVM; IMU sensor; BLE

Charpter 1 - Introduction

1.1 Background

According to WHO, Fall has been the second leading cause of unintentional injury deaths worldwide [1]. The most ideal solution is to prevent falls from happening.

As a result of losing balance, falls can be detected and stopped when their trend appears but is still not too obvious. With various fall detection systems developed, many of them detect after-impact falls and are incompetent for fall prevention. Therefore, an early-fall detection system that detects falls in time is in need. Fall detection systems developed can be classified into sensing systems based on environment and wearable sensing systems [2]. Considering the cost, accuracy and convenience for home use, a wearable smart sensing system for early-fall detection was chosen for the research and development of the project.

This project has proposed a wearable smart sensing system for early-fall detection. In this project, a quantitative analysis was carried out. Raw data were collected from sensing units fixed on a participant. The development steps following were IMU data collection of three types of activity, ECOC-SVM classification models training, models' implementation into sensing units, data collection and analysis for classification results of different sensing units, weight matrix design for central control and the system verification of the completed system.

Nano RP2040 connect was the sensing unit chosen and was powered by a lithium micro-battery through a micro-USB cable. MATLAB r2021a in Windows10 supported the central control and provided machine learning tools for training SVM models.

Ethical approval has been considered. The participant was also the developer of this report who has experience in self-protection. The system was designed to run under a voltage which is safe for the human body. Active sensors were not involved in the system. Protection devices had been introduced during the experiments. The system developed will be used for the protection of people's health and safety.

1.2 Aims

The system designed in the project is a wearable smart sensing system for early-fall detection that should be able to detect falls in 300ms - 500ms after the fall has begun. Experiments for data collection and system verification should be performed by humans rather than dummies or computer simulations.

1.3 Objectives

1. To complete a literature review of existing solutions for reference.
2. To choose the most ideal plan of sensor-algorithm combination.
3. To choose wearable hardware to carry the control system.
4. To build a wireless communication net for data transformation.
5. To collect data on three activities, fall forward, fall backward, and walk.
6. To build an algorithm model for early fall detection and classification.
7. To verify the function of the system through experiments.

1.4 Project Report Layout

Chapter 1: An introduction of the study's importance and potential as well as motivation, methodology, aims, objectives, and report layout.

Chapter 2: A literature review of early fall definition, existing fall detection systems and some related technologies that will be used in the design.

Chapter 3: Total design of the sensing system, including the design's objectives and function structure followed by the detail of hardware and software.

Chapter 4: The system's development process includes five steps, sensors fixing, BLE communication net development, data collection, SVM models training and development of the complete system.

Chapter 5: System verification through human experiments with results, analysis, and discussion.

Chapter 6: A conclusion of the study's achievement, discoveries, limitations and plan for future study.

Charpter 2 - Literature Review

2.1 Introduction

In this chapter, the definition of the early-fall process will be firstly analyzed according to the research on the process of falls. Then, the existing projects of fall detection systems, especially the fall detection algorithms and their supporting sensors, need to be studied and compared to provide experience for the total design. After the selection of algorithms and sensors, the chosen will be analyzed in a more detailed way for the specific development and implementation of the system.

2.2 The Process of Early-Falls

The existing fall detection method can be divided into two types, fall detection before the fall and after the fall [3]. The early-fall process belongs to the former which is around 900ms after the falls start according to the research summary by X.Y. Hu and X.D Qu [4]. However, the precise time the early-fall process cost has not been measured while the definition of the obvious trend of fall has not been clear.

The former studies should be reviewed for a reasonable definition of the early-fall process. X.Y. Hu et al. [5] reported a fall detection method based on the ARIMA model and activity Analysis Eagle System as well as the time spent for fall detection, 600 - 700 ms. Another system by D. Martelli [6] based on neural network and SENLY platform has given a shorter mean detection time of 351 $\pm$ 123 ms. In 2008, a system using IMU and threshold method has been proposed by M.N. Nyan et al. [7] and has been able to detect falls in 700ms before the impact, in other words, about 200 ms after the fall trend appears. According to the time cost of fall detection in previous systems, the early fall process takes $500\,ms \pm 200\,ms$ after fall starts.

2.3 Existing Sensing Systems for Fall Detection

Fall detection systems have been widely studied. For the systems developed, the choice of sensors and algorithms is the key to realizing the fall detection function and the decisive factor in the system's performance. Fall detection algorithms and sensors should be reviewed respectively.

2.3.1 Fall Detection Algorithms

The fall detection algorithms can process data from the sensors to find whether the fall occurs or not. In fact, for the same input data, the efficiency and accuracy of classification by different algorithms can be various.

The threshold method is the most frequently used method in the field of fall detection and prevention [8]. To clarify the boundary of fall and balance by setting fixed values which almost determine the quality of classification, experiments have been done to measure the features of bodies during the process of falls. Physical models of gait balance have also been introduced. A system based on the accelerometer in a smartphone was proposed by S. Abbate et al. [9] who set the acceleration of 3g detected on the waist as the threshold of fall detection. S.B. Wang et al. [10] developed a system which classifies falls and activities of daily living by setting three levels of thresholds for the acceleration signal magnitude vector of the human body for fall detection. With the advantage of high speed and few calculations needed, fall detection methods based on threshold are questioned because of the accuracy. The choice of fixed thresholds is important for improving the efficiency of threshold-based methods and methods for determining the proper threshold levels for algorithms should be studied [11]. However, there has also been an opinion suggesting that this kind of method failed to detect falls accurately [12].

The development of machine learning and deep learning has provided a new option for the study of fall detection. Most of the current mainstream machine learning algorithms have been discussed and applied to fall detection systems. In the fall detection project by P. Salgado et al. [13], SVM was introduced to perform a binary classification for data which was collected by a tri-accelerometer sensor and incorporated by a model of the body pose. S.C. Li et al. [14] proposed an early fall detection system based on a 3D convolutional neural network (CNN), achieving 100% accuracy of detection within 500ms after falls start. The quality of the fall detection model trained by machine learning depends on not only the algorithms but also the data provided for training. The research by A. Kariluoto et al. [15] has shown that significant features can optimize the models significantly while more data may not lead to more accurate models. However, fall detection methods based on machine learning often demand considerable computing capability as well as storage volume [16]. The systems need smartphones, high-performance microcomputers and even PC to support algorithms based on machine learning.

It is meaningful to combine these two methods with obvious and complementary advantages and disadvantages. T. Xu et al. [17] proposed a wearable fall detection system whose algorithm combines threshold-based method and CNN and achieved an accuracy rate of 97.46%. A. Shahzad et al. [18] developed a smartphone-based fall detection system in which threshold-based method (TBM) and multiple-kernel-learning SVM is used and achieved an accuracy of 97.8% as well as the lowest false alarm rate to date. The combination methods are suitable for situations in which the data and time are limited while the accuracy should be guaranteed.

2.3.2 Sensors

Sensors are data providers of algorithms. For data from various sensors, their types, features, and quality can be different while they can always be trained and classified by machine learning or be judged by thresholds set for them. Sensors used in the fall detection field can be divided into two groups: wearable sensors and environment-based sensors.

Wearable sensors which have lightweight and small sizes enable the design of wearable fall detection systems. In 2002, D. Sherrill et al. [19] discussed a wearable system using surface electromyography (EMG) and accelerometry (ACC) after comparison of their sensors and sensitivity. In 2018, a 9-axis motion tracking sensor containing an accelerometer, gyroscope and magnetometer was introduced in energy efficient wearable sensor node developed by TN Gia et al. [20] for fall detection. With various wearable sensors developed through time, inertial measurement units (IMU) are widely used in fall detection [21]. Wearable fall detection systems can be flexibly applied to indoor or outdoor environments and detect falls without being disturbed by obstacles in the environment. However, these systems should always be worn in daily life. Therefore, whether wearable devices are comfortable and convenient are factors that must be considered. Besides, the shaking of wearable devices carrying sensors such as clothes brings unavoidable noise for detection.

Various sensing systems based on the environment can be used as fall detection systems after specialized development. Microsoft Kinect® depth sensor set on the ceiling has been used by S. Gasparrini et al. [22] to detect one or more human subjects by analyzing depth frames. A fall detection system using six Raptor-4 cameras has been developed by XC Wang et al. [23] to classify falls from activities of daily living by using motion capture data and a novel model trained by SVM. Being free from the limitation of size and weight of sensors and control systems, fall detection systems based on the environment show tremendous possibilities for fall-detection methods. Unlike wearable systems, environmental-based systems have great potential in the field of multi-subject fall detection. However, their shortages are also obvious. To realize their function outside the laboratory environment, multiple expensive devices of fall detection systems should be settled in ideal locations around the indoor environment so that corners which cannot be detected will not exist. Such requirements cannot be accepted by most users.

2.4 IMU Sensors

Among sensors that have been used in fall detection systems, IMUs (inertial measurement units) are the most widely used, proving their feasibility in fall detection. As sensors for a wearable system, IMUs have shown their advantage in cost and size. As a considerable choice for the project, a further literature review about IMU should be done.

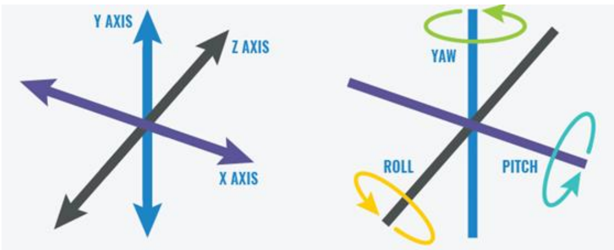

Figure 2- 1: Six Degrees of Freedom [24]

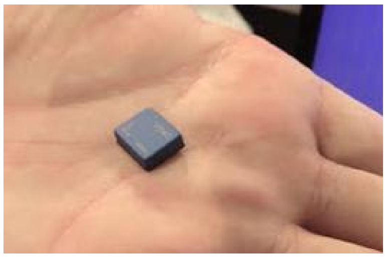

Figure 2- 2: MEMS IMU [25]

IMU refers to a type of sensing unit that can measure its translations, rotations, and velocities in space [26]. To realize basic functions, an IMU usually contains a three-axis accelerometer and a three-axis gyroscope that output two groups of raw data, Ax, Ay, Az which belong to the acceleration group and Gx, Gy, Gz which belong to the gyroscope group. Figure 2-1 shows the six degrees of freedom measured.

As Figure 2-2 shown, among the mainstream IMU sensors, IMU based on Micro-Electro-Mechanical System has shown more and more advantages in its size, price, environmental adaptability, and accuracy during its development in recent years [27]. However, the problem of angular random walk of the gyroscope has an impact on MEMS IMU. According to the review of existing fall detection studies, MEMS IMU is most frequently used in IMU-based plans of fall detection while other types of IMU are rarely used. However, it should be mentioned that a combination plan of MEMS IMU and FOG IMU has been proposed by J.Z Lu et al. [28] as a calibration method to reduce error. The research shows the advantage of the multi-IMUs design.

2.5 SVM and ECOC

Machine learning methods have been used in fall detection for data classification. A comparison of five common fall detection algorithms has been made by O. Aziz et al. [29] who found that the support vector machine (SVM) provided the greatest sensitivity and specificity of 96 % when it classifies falls and non-falls. Further understanding of SVM should be made.

SVM [30] is developed for binary classification by building a hyperplane, which can be described by a function, as the decision boundary of two types of data that have been seen as vectors in high dimensional space. However, any plane cannot classify the two groups of data if they are not linearly separable in space. In this situation, a kernel function [31] that also represents a plane should be designed based on a higher dimension in which the two groups of data can be linearly separable. According to the hyperplane separation theorem by Hermann Minkowski, a hyperplane can always be found to classify two disjoint convex sets. Therefore, SVM can classify any two disjoint sets. The kernel functions that realize classification functions are just function expressions that can be easily embedded in most of the programmable platforms without any additional frame. However, the higher the dimension of the hyperplane, the longer the time it takes to classify the data.

Figure 2-3 shows how the SVM classification works by using the kernel method.

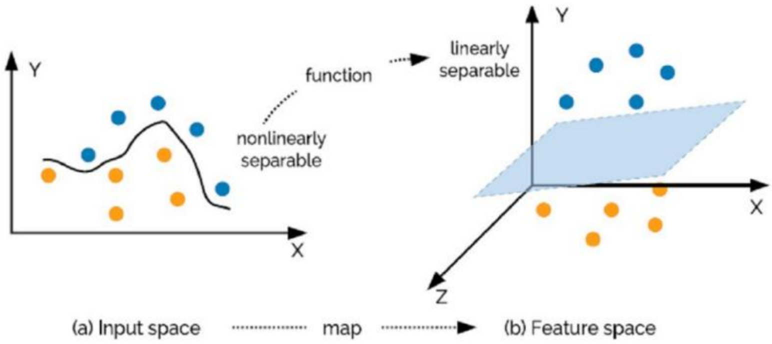

Figure 2- 3: Kernel Method of SVM [32]

However, the fall detection system is designed to detect and classify different types of falls. Thus, a multi-class classifier is required while SVM is only for binary classification. Error-correcting Output Codes (ECOC) is a multiclass-to-binary reduction framework that transforms the multi-class classification problem into several binary classification problems [33]. A combination of ECOC and SVM can meet the requirement of the system to be designed.

A coding matrix should be built for ECOC classification according to the classification method chosen. The two most common methods are One Against All (OAA) and One Against One (OAO) [34]. As Figure 2-4 shown, OAA, the simplest approach of ECOC, realizes the binary classification between every class and the rest while OAO builds binary learners between every two classes.

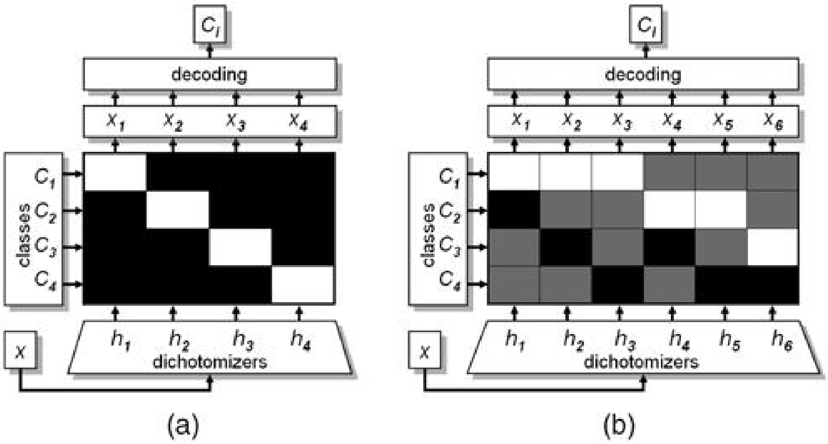

Figure 2- 4: Coding of OAA Method And OAO Method [35]

With various ECOC methods developing, the basic ECOC can be automatically encoded by providers of machine learning plans like MATLAB.

The combination of ECOC and SVM has been proved to be a reliable solution for multi-class classification. The verification method of the accuracy of computer simulation models based on ECOC has been reported by Y Zhou et al. [36] as well as the accuracy of 82.3%. ECOC-SVM has also been used to classify different mental stress levels by F. Al-shargie et al. [37] and average classification accuracy of 94.79% has been achieved.

According to the research on ECOC-SVM by ZG Yan et al. [38], the performance of ECOC-SVM is determined by the performance of its corresponding sub-SVM classifiers while the performance of ECOC is secondary. It means that the length of ECOC code can be limited if models trained by SVM are of high quality, which shows its advantage in the fall detection process that requires high-speed calculation.

2.6 Bluetooth Low Energy

Bluetooth low energy (BLE) is an energy-saving Bluetooth that is built for IoT sensors which perform discontinuous short data transmission [39]. It requires little energy compared with classic Bluetooth while remains a communication range of 80 meters [40], making it suitable for wireless wearable devices. However, it should be mentioned that sharing raw data in real-time continuously is not what BLE is designed for.

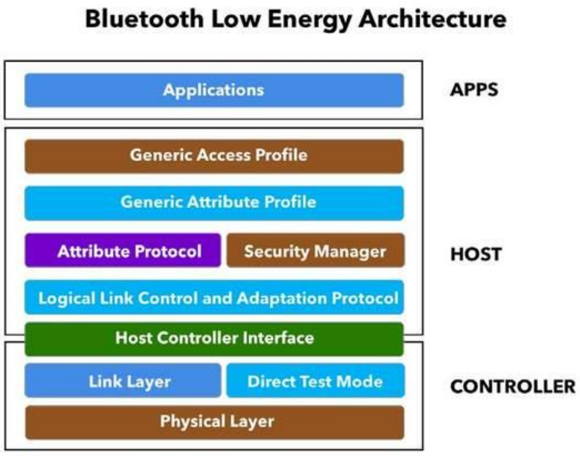

Figure 2- 5: BLE Structure [41]

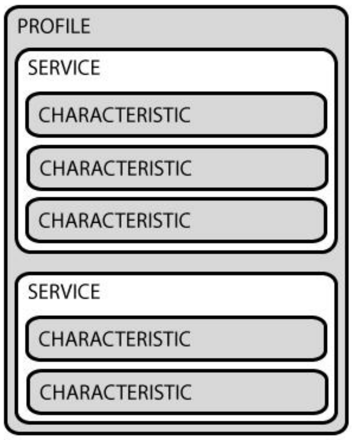

Figure 2- 6: GATT Structure [42]

Figure 2-5 shows the complete structure of BLE which has been integrated into libraries by many platforms. In most cases, developers only need to focus on the development of GATT shown in Figure 2-6 which supports only one-to-one data transportation and essentially.

Security of BLE v4.2 can be protected by Elliptic-curve Diffie-Hellman (ECDH) protocol for security key generation [43].

2.7 Discussion

In this literature review, the definition of early fall as well as the goal that the system is expected to achieve has been discussed. Several existing fall detection systems, especially common fall detection algorithms and sensors, have been reviewed. Four technologies, IMU, ECOC, SVM and BLE, have been specifically studied and discussed. According to the literature review, fall detection systems have been widely studied and implemented in a variety of ways, providing useful references for the objectives and overall design of the system in this project.

Fall detection systems are designed for either pre-impact detection or post-fall detection. The early fall detection studied in this project belongs to pre-impact detection that has more stringent requirements. At present, the early fall process has not been clearly defined. According to the literature review of the fall process and the experience of the fall detection experiment in the study, it is reasonable to define early fall as within 500ms after the start of a fall.

According to the algorithms reviewed, the combination of machine learning and threshold method is a promising development direction for the fall detection algorithm that should be adopted in this project.

The environment-based sensors are expensive for most users and easy to be blocked in the indoor environment, so they are not suitable for home use. Wearable sensors are light and relatively cheap, making them a better choice for this project.

IMU has been widely used and studied in wearable fall detection systems. Its functionality has been fully verified. In this project, IMU units are supposed to be fixed on not only the back of the waist but also on ankles that have a limited place for sensing units. The system for home use works in the indoor environment without extreme temperature or obvious vibration. To ensure the safety and comfort of long-term wear, the requirement for the power supply should be as small as possible. Among the three types of IMU reviewed, MEMS IMU is the most suitable for this project though it has an accuracy that is lower than others.

SVM has been considered a fast classification method. With ECOC, the models trained by SVM can efficiently and accurately solve multi-classification problems. An ECOC-SVM classifier composed of multiple kernel functions can be implanted into various platforms. According to the review, the ECOC-SVM method is fully qualified for being the core algorithm of this project.

BLE provides a low-energy-required wireless communication network for fall detection systems with sufficient security, enabling it to establish wireless connections with actuators that also have BLE and IoT platforms like e-health cloud servers. The communication network of the system should be based on BLE for its further development.

Charpter 3 - Overall Design

3.1 Introduction

This chapter introduces the overall design of the early fall detection system. First, the expected functions of the system are proposed. Next, the structure of the system, including the sensors selection and collaboration and the fall detection algorithm structure, is shown in the function diagram. Then, the hardware and software parts are introduced in detail. Finally, the realizability, cost and user requirements of the system are discussed.

3.2 Expectations of The Design

The project aims to design a wireless wearable home-use fall detection system for early fall detection. The expectation of the design is shown below.

1. The system should detect and classify falls within 500ms after falls start.
2. The system's accuracy in fall detection and classification should be at least 80%.
3. The system should be portable for different actuators and wearable devices.
4. The overall cost of the system should be less than 200 pounds.

3.3 Functional Structure

The early-fall detection system is based on six sensing units fixed on selected locations on the user's body and a central control based on a PC. Each of the sensing units receives raw data from its own IMU and performs fall detection and classification independently. Then the detection and classification results are reported to the central control which will decide the result and report to actuators or IoT servers. The communication between the nodes and the central control (CC) is based on BLE.

Figure 3-1 illustrates the structure as well as the data flow of the system designed.

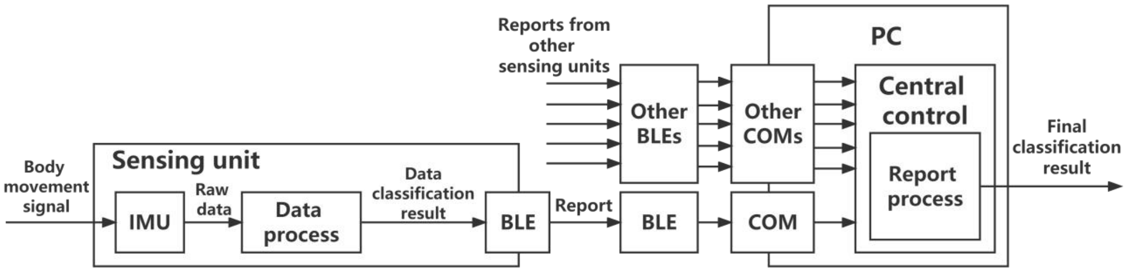

Figure 3- 1: Overall System Design

3.4 Hardware Design

3.4.1 Sensing Unit

Nano RP2040 connect is selected as the hardware part of the sensing units. Being launched in 2021, it is an 18mm x 45mm MCU that integrates Raspberry Pi RP2040 Microcontroller, 6-axis IMU, native Bluetooth® and Wi-Fi module and other practical tools with an input voltage of 5-18V only [44]. It provides IMU sensors and a Bluetooth module that also supports BLE, so it meets the functional requirements of the system. Figure 3-2 shows a 5V mini power bank, a sensing unit and a Nano RP2040 connect.

Figure 3- 2: A Mini Power Bank, A Sensing Unit and A Nano RP2040 Connect

3.4.2 Location of The Sensing Units

Since IMU sensors have been widely used and tested, the best locations chosen in this system for fall detection have been concluded from existing studies. According to the research of G.Y. Shi et al. [45], C.C. Li et al. [46] and K. Bharathkumar et al. [47], the sensing units should be fixed on the chosen locations which are the nape, lumbar, lateral knees, and ankles. Figure 3-3 shows the locations of sensing units.

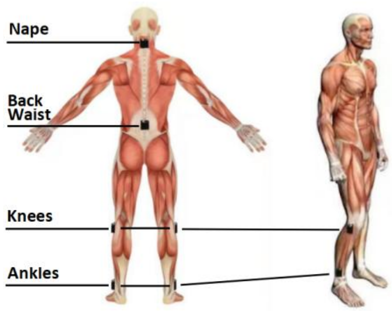

Figure 3- 3: Locations of Sensing Units

3.5 Software Design

3.5.1 Overall Design of Data Processing

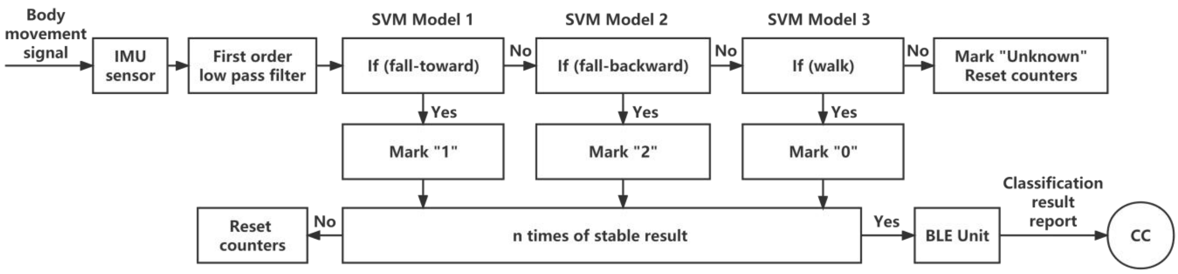

Figure 3- 4: IMU Data Processing in Sensing Units

Figure 3-4 introduces the detail of data processing in a single unit. The actions of participants are monitored in real-time by the IMU sensor which outputs the 6 data that describe the 3-axis acceleration and angular velocity.

To eliminate the interference caused by the tremble of sensors, the following first-order low-pass filter is set to process the raw data:

$$processed\_data = factor \times raw\_data + (1 - factor) \times last\_processed\_data$$

The effect of the filter depends on the $\boldsymbol{factor}$ which is defined as:

$$factor = 2 \times \pi \times cut\_off\_frequency \div sampling\_frequency$$

The ideal sampling frequency and cut-off frequency should be set and adjusted during the experiments.

Since the sample and classification frequency can be over 100Hz, the situation that unstable classification results are given by SVM models may occur due to environmental interference. A stable window n should be set as the boundary condition of counters that record the time that the same classification result is given continuously. Therefore, the stability of the system can be improved.

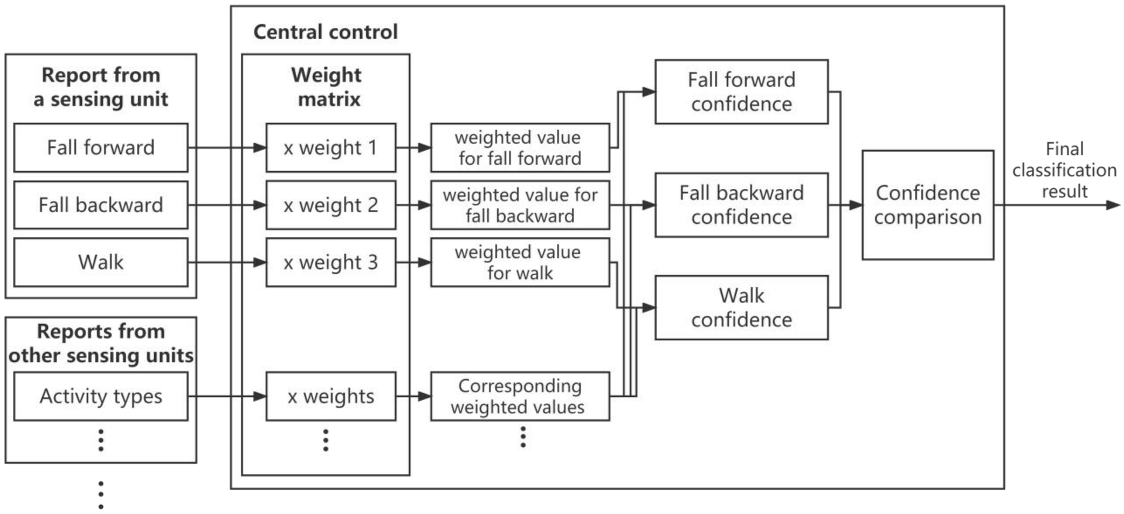

Figure 3- 5: Report analysis in the central control

Figure 3-5 shows the functional structure of the central control. The reports received by the central control will contribute to the confidence value of corresponding activities after being given a particular weight in the weight matrix.

3.5.2 Fall Detection and Classification Model

The three models the data should go through are linear kernel functions that represent fall-forward detection, fall-backward detection and walk detection. For each of them, the equation of the kernel function can be expressed as:

$$score = \sum_{i=1}^{6}\left(Beta_i \times \left(IMUdata_i - Mu_i\right) \div Sigma_i\right) + B\text{ias} \qquad [48]$$

$$IMUdata = \{Ax, Ay, Az, Gx, Gy, Gz\}$$

$$Beta, Mu, Sigma, B\text{ias} : \textit{Parameters given by ECOC-SVM training}$$

The ECOC matrices have always been:

	score1	score2	score3
fall toward	1	−1	−1
fall backward	−1	1	−1
walk	−1	−1	1

Table 3- 1: ECOC Matrix

The coding matrix in table 3-1 shows that a positive value will be given by a score when the corresponding activity is detected. Ideally, only one of the scores should be greater than 0 during a classification. When the scores above 0 become more than one, the classification result will be given by the greatest score.

3.5.3 BLE Communication Net

The BLE communication net is built for the transportation of falls as well as their types reported by sensing units and the final fall detection and classification result from the central control. The raw data collected by IMU will not be transported on the net. The BLE communication network in the report is shown in Figure 3-6.

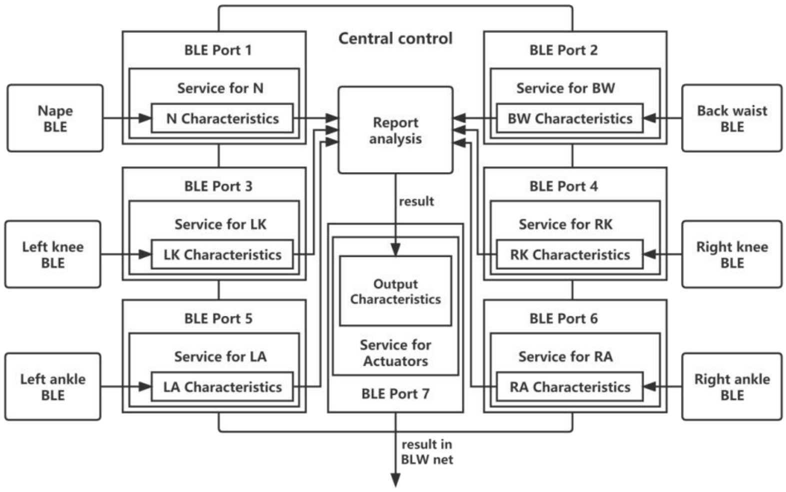

Figure 3- 6: BLE Communication Net of Early-Fall Detection System

In the communication system shown in Figure 3-6, every sensing unit has provided a port in the PC for BLE connection.

After the connection between two devices is established temporarily, the 3-levels security process in Figure 3-7 is initiated.

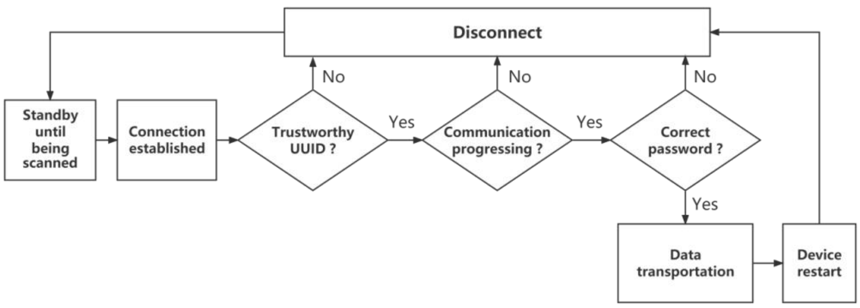

Figure 3- 7: BLE Verification Process for Security

For every pair of devices, the only trustworthy UUID and password have been saved on both sides for verification in level 1 and level 3. The level 2 was designed to prevent the unexpected third device from interfering in the communication. After the 3 levels of verification, the connection will remain until the restart of the devices.

3.6 Discussion

The early fall detection and classification system was designed based on multi IMUs and the idea of maximizing the number of samples collected and classified within the limited time of the early-fall process. The ideal sample sampling frequency is 100Hz.

The six sensing units should be tightly fixed on particular locations on the body for the accuracy of data collection. Instead of other wearable devices, sellotape should be used to fix the units during the experiments.

It can be predicted that sensors in different locations on the body show more advantages in detecting and classifying specific types of falls while performing badly when it comes to other types. Therefore, a weight matrix that decides the degree of confidence of different units toward different activities must be built.

The classification method of the system belongs to machine learning. Three models perform fall detection and classification one by one and each of them can finish a classification within milliseconds. As models for detecting more types of falls are introduced, the frequency of data acquisition might be lower and lower. This possible problem should be studied further during experiments.

The cost of each sensing unit, including the MCU, mini power bank and short cable, is 30£. The total cost of the system is 190£ which is within the budget of 200£.

The system design is powered by 5V DC using passive sensors. The size of the sensing unit makes it easy to be wrapped in wearable devices so the sharp part of the hardware won’t contact the users. Thus, the design is in accord with ethical approval.

Charpter 4 - Design Development

4.1 Introduction

This chapter introduces the whole development process of the early-fall detection system including experiment methods, discoveries and problems that occurred. Examples of system operation will be presented, and experimental records can be found in the appendix.

4.2 Total Design

The system was developed in three steps, data collection, activity classification models training and system building. As Figure 4-1 shown, the third step can be finished after repeating data collection and model retraining.

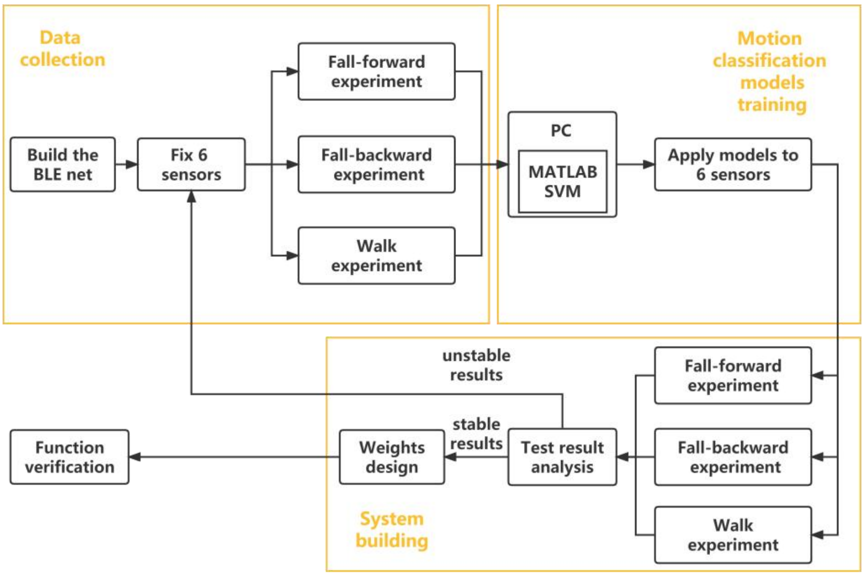

Figure 4- 1: Development Process of The Early-Fall Detection System

4.3 Data collection

Figure 4-2, Figure 4-3 and Figure 4-4 have shown the six units that were fixed on the nape, back waist, lateral knees, and ankles to avoid the jitter of clothes that would have a serious impact on data quality.

Figure 4- 2: Lower limb sensing unit *Figure 4- 3: Nape sensing unit* *Figure 4- 4: Back waist sensing unit*

The BLE connection net was established before the experiments so the sensing units could be read in PC. Figure 4-5 and Figure 4-6 have shown the fall experiments. Data collected were sent to the PC as Figure 4-7 shown. The security verification of BLE has been tested in Figure 4-8. The whole connection process takes about 10 seconds.

Figure 4- 5: Fall Forward

Figure 4- 6: Fall Backward

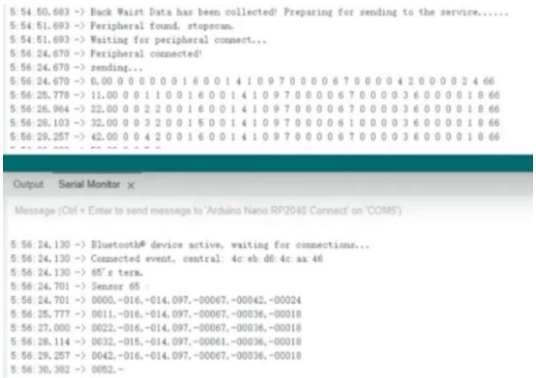

Figure 4- 7: Data Transportation Through BLE

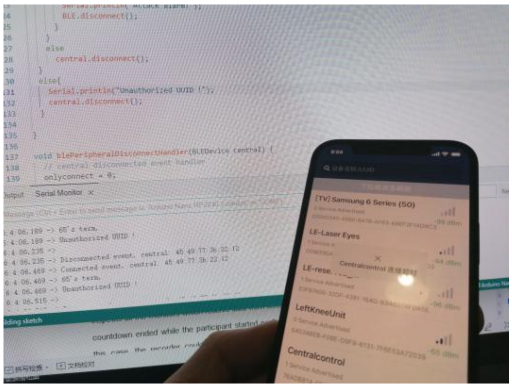

Figure 4- 8: BLE Verification Denied

When the six sensing units started collecting data synchronously, the error of start time between different units could reach 500 ms, making it impossible to evaluate the sensitivity of the sensors. Therefore, a recorder that inspected all the monitors receiving data from sensing units was set. It was initiated after its countdown ended while the participant started performing fall at the same time. As Figure 4-9 shown, the recorder could record the exact data of the six units when the record started and enabled the data clipping for synchronizing the start time of the six records.

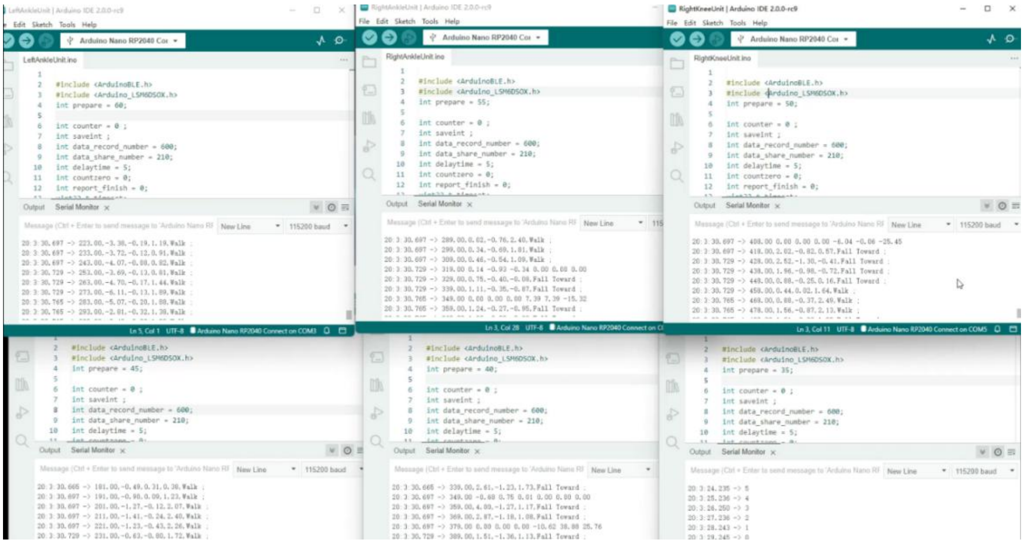

Figure 4- 9: A Record of Data at The Beginning of a Fall

All the data that were collected after the units started would be saved in sensing units and sent to the PC. The data collected within 6000ms after the record began would be saved in sheets while the first 3000ms would be selected to train the SVM models.

Although the collection took only 3 seconds, it spent minutes transporting all the data from the unit to the PC through BLE. To improve the speed of data collection, USB cables were introduced between the sensing units and the PC.

For each of the three types of activity, 10 sets of data were collected for ECOC-SVM model training.

4.4 Activity Classification Models Training

The data saved in sheets were processed by the ECOC-SVM machine learning tool, ***fitcecoc*** [49] provided by Matllab.

Model = fitcecoc(input,target,'Coding','onevsall','Learners',t);

input: matrix containing IMU data of three types of activities.

target: self-built matrix to clarify data in input matrix correctly.

Onevsall: a coding method in which every type of activity owns a particular SVM model to select it out of three activities.

t: Fit template for classification SVM provided by MATLAB

According to the instruction above, the fitcecoc combines input set and target set into the training set to build the linear kernel functions through the SVM method. Figure 4-10, Figure 4-11 and Figure 4-12 have shown the machine learning result of the right knee sensing unit as an example.

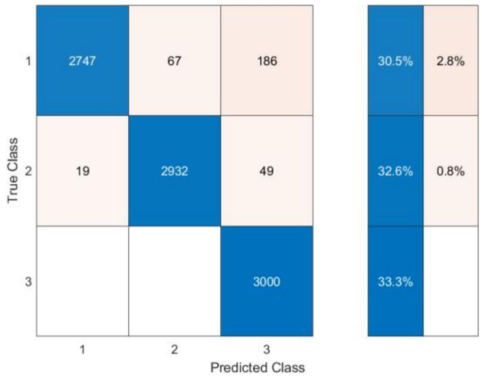

Figure 4- 10: Confusion Matrix of SVM Classification

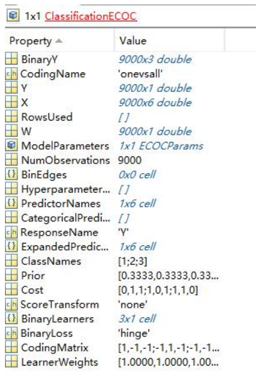

Figure 4- 11: ECOC-SVM Result

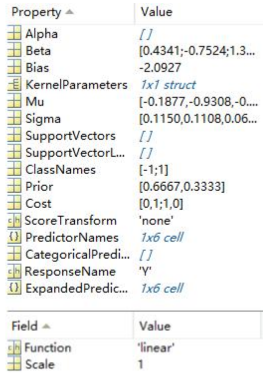

Figure 4- 12:Model of Fall Backward Detection

According to Figure 4-10, the theoretical accuracy of the model can be considered 96.4%. In Figure, key parameters of the SVM model, Beta, Mu and Sigma can be clearly seen while the type of the kernel function has been shown in Kernel Parameters. An SVM model can be accomplished with the parameters above and can be implanted into the MCU of the sensing units for fall-forward detection and classification.

4.5 System Building

With 18 SVM models built for 6 sensing units to classify 3 types of activity, the complete fall detection and classification system can be built. Figure 4-13 shows an example of SVM models in Nano RP2040 connection compiled by Arduino IDE 2.0 and Figure 4-14 presents an example of the data classification process.

```
// Left Knee (LK) parameters input
// Parameters for model 'Fall-forward or not'
float sensitivity1 = -0.2;
float Mu1[6] = {-0.2451,0.5567,-0.2076,-0.5522,-0.7769,-4.3962};
float Sigma1[6] = {0.4953,0.4413,0.2823,9.6756,17.3983,30.7211};
float Beta1[6] = {5.6625,2.4891,2.6952,-0.9580,-2.0591,5.8375};
float Bias1 = -0.4817;
// Parameters for model 'Fall-backward or not'
float sensitivity2 = -0.2;
float Mu2[6] = {-0.2451,0.5567,-0.2076,-0.5522,-0.7769,-4.3962};
float Sigma2[6] = {0.4953,0.4413,0.2823,9.6756,17.3983,30.7211};
float Beta2[6] = {-1.1766,-3.1505,-1.8526,-0.0926,-0.3442,-0.4704};
float Bias2 = -0.4745;
// Parameters for model 'Walk or not'
float sensitivity3 = -0.2;
float Mu3[6] = {-0.2451,0.5567,-0.2076,-0.5522,-0.7769,-4.3962};
float Sigma3[6] = {0.4953,0.4413,0.2823,9.6756,17.3983,30.7211};
float Beta3[6] = {-5.6540,5.4570,1.4534,0.1937,1.6887,-0.9183};
float Bias3 = -3.8697;
```

Figure 4- 13: Parameter Input

```
// Left Knee: Calculation for SVM classification. Positive if result (score) > 0.
// score model for Fall-Forward or not
for (scorei = 1;scorei <= 6;scorei ++){
  score1 = score1 +  ((datacollection[counter][scorei] - Mu1[scorei - 1])
  / Sigma1[scorei - 1] * Beta1[scorei - 1]);
}
score1 = score1 + Bias1;
// score model for Fall-Backward or not
for (scorei = 1;scorei <= 6;scorei ++){
  score2 = score2 +  ((datacollection[counter][scorei] - Mu2[scorei - 1])
  / Sigma2[scorei - 1] * Beta2[scorei - 1]);
}
score2 = score2 + Bias2;
// score model for Walk or not
for (scorei = 1;scorei <= 6;scorei ++){
  score3 = score3 +  ((datacollection[counter][scorei] - Mu3[scorei - 1])
  / Sigma3[scorei - 1] * Beta3[scorei - 1]);
}
score3 = score3 + Bias3;
// If more than one score > 0, the largest score will claim the result
// None > 0, output 'Unknown'
score1 = score1 + sensitivity1; // Fall-Forward or not
score2 = score2 + sensitivity2; // Fall-Backward or not
score3 = score3 + sensitivity3; // Walk or not
```

Figure 4- 14: Kernel Functions for Classification

```
22:36:41.430 -> Time(ms): 107.00 FF: -1.39 FB: -0.13 W: -1.93 Classification: Unknown
22:36:41.430 -> Time(ms): 117.00 FF: -1.33 FB: -0.17 W: -1.89 Classification: Unknown
22:36:41.430 -> Time(ms): 127.00 FF: -1.25 FB: -0.17 W: -1.97 Classification: Unknown
22:36:41.465 -> Time(ms): 137.00 FF: -1.24 FB: -0.16 W: -2.08 Classification: Unknown
22:36:41.465 -> Time(ms): 147.00 FF: -1.43 FB: -0.12 W: -2.04 Classification: Unknown
22:36:41.496 -> Time(ms): 163.00 FF: -1.59 FB: -0.01 W: -1.89 Classification: Unknown
22:36:41.496 -> Time(ms): 173.00 FF: -1.63 FB: 0.04 W: -1.83 Classification: Fall Backward
22:36:41.496 -> Time(ms): 183.00 FF: -1.81 FB: 0.14 W: -1.84 Classification: Fall Backward
22:36:41.496 -> Time(ms): 194.00 FF: -1.77 FB: 0.20 W: -2.26 Classification: Fall Backward
22:36:41.532 -> Time(ms): 204.00 FF: -2.01 FB: 0.34 W: -3.17 Classification: Fall Backward
22:36:41.532 -> Time(ms): 214.00 FF: -2.25 FB: 0.61 W: -4.40 Classification: Fall Backward
22:36:41.563 -> Time(ms): 230.00 FF: -2.06 FB: 0.91 W: -5.98 Classification: Fall Backward
22:36:41.563 -> Time(ms): 240.00 FF: -1.74 FB: 0.83 W: -6.18 Classification: Fall Backward
22:36:41.563 -> Time(ms): 250.00 FF: -1.74 FB: 0.79 W: -5.89 Classification: Fall Backward
22:36:41.563 -> Time(ms): 260.00 FF: -0.87 FB: 0.92 W: -5.40 Classification: Fall Backward
22:36:41.595 -> Time(ms): 270.00 FF: 1.46 FB: 0.68 W: -5.34 Classification: Fall Toward
22:36:41.595 -> Time(ms): 280.00 FF: 3.71 FB: 0.27 W: -5.60 Classification: Fall Toward
22:36:41.595 -> Time(ms): 291.00 FF: 3.83 FB: 0.24 W: -5.49 Classification: Fall Toward
22:36:41.628 -> Time(ms): 301.00 FF: 3.07 FB: 0.28 W: -5.04 Classification: Fall Toward
22:36:41.628 -> Time(ms): 311.00 FF: 1.64 FB: 0.56 W: -4.91 Classification: Fall Toward
22:36:41.660 -> Time(ms): 326.00 FF: 0.14 FB: 0.53 W: -4.22 Classification: Fall Backward
22:36:41.660 -> Time(ms): 336.00 FF: -1.51 FB: 0.72 W: -3.95 Classification: Fall Backward
```

Figure 4- 15: SVM Classification During a Fall Backward Process

As Figure 4-15 shown, data were classified in real-time after the collection began. The models would be inaccurate if the classification result was too unstable, or the rate of misclassification was too high, and retraining would be required. Besides, the change of classification result caused by vibration interference and wrong classification can be observed in Figure 4-15, suggesting that the stable window, n is demanded. When a stable result was reported over n times, the result would be sent to central control by BLE.

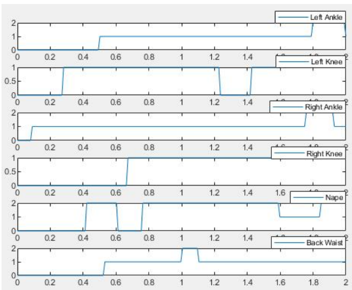

Figure 4- 16: CC Receiver Inspection (n = 10)

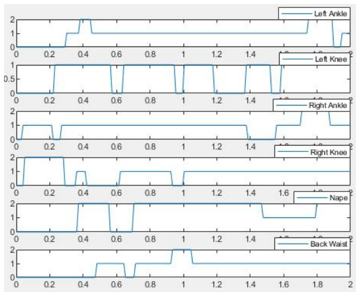

Figure 4- 17: CC Receiver Inspection (n = 5)

Figure 4-16 and Figure 4-17 have illustrated the classification results received by the central control (CC) during the first 200ms of a fall-forward process when n set in sensing units was different. In the two figures,0,1,2 represents walk/unknown, fall forward and fall backward respectively. As n became smaller, the sensitivity and speed of detection grew while the stability and accuracy of the report decreased. Besides, the difference in sensitivity, stability and accuracy between sensing units have been shown. The weight of confidence for every unit would be set according to the results of 20 experiments in which the situation of every unit within 500ms will receive special attention.

4.6 Summary

In this chapter, the development process of the system based on quantitative research has been reviewed in detail. Sensors' fixing, BLE verification, raw IMU data transmission, ECOC-SVM model foundation, activities classification of sensing units and reports received by central control have been presented by several real-time records and results.

Data used in the development process were collected by IMU sensors on participants and transmitted through BLE. The hardware of sensing units has been proved to be enough for achieving the expectation while the software of the units was completed using Arduino IDE 2.0. The central control (CC), as well as the model training process, were based on Matlab in PC. The CC can be transplanted into MCU or smartphones with ease since no additional frames or libraries are required.

A problem during the raw data collection process has been reported. The IMU sensor of Nano RP2040 often returns null values when the frequency of data collection is too high. The frequency has been set as 100Hz by adding a 5 ms delay into the fall detection process so few wrong data will be reported. According to the test, an additional kernel function cost about 0.6 ms for calculation. Theoretically, when the 5 ms of delay is fully made use of, it can support at most eight additional activities to be classified by this system.

Charpter 5 - Experiment Result and Data Analysis

5.1 Introduction

This chapter will introduce the result of all the parameters designed for the system. Then, experiments and standards for functional verification of the system will be designed and discussed. Finally, the chapter will present the results of the system verification and the evaluation of the system performance.

5.2 Parameter Design

ECOC-SVM models for the classification of fall forward (FF), fall backward (FB) and walk (W) have been built for every sensing unit as Table 5- 1 shown.

Unit	SVM	Parameter	P1	P2	P3	P4	P5	P6
Nape	N-FF	Mu	-0.0704	-0.8262	0.3930	-1.0788	-6.9046	4.7421
		Sigma	0.0647	0.1763	0.2006	11.8487	17.6259	7.9501
		Beta	0.4835	0.5655	0.3966	3.7910	-2.0655	-4.1996
		Bias	-2.5340					
	N-FB	Mu	-0.0704	-0.8262	0.3930	-1.0788	-6.9046	4.7421
		Sigma	0.0647	0.1763	0.2006	11.8487	17.6259	7.9501
		Beta	-0.1872	0.7185	-1.8052	-4.7119	8.7949	2.9314
		Bias	-0.6148					
	N-W	Mu	-0.0704	-0.8262	0.3930	-1.0788	-6.9046	4.7421
		Sigma	0.0647	0.1763	0.2006	11.8487	17.6259	7.9501
		Beta	-0.1494	-4.6892	2.6975	-0.6095	-8.0737	5.7565
		Bias	1.2943					
Back waist	BW-FF	Mu	-0.0448	-0.8583	-0.0384	1.9188	-3.4383	0.6626
		Sigma	0.0421	0.2199	0.2003	15.9371	7.4354	3.3386
		Beta	0.1032	0.4399	-1.2432	4.9699	0.9447	-0.9654
		Bias	-0.8449					
	BW-FB	Mu	-0.0448	-0.8583	-0.0384	1.9188	-3.4383	0.6626
		Sigma	0.0421	0.2199	0.2003	15.9371	7.4354	3.3386
		Beta	0.8664	1.8378	0.3378	-8.6790	2.8270	-1.1957
		Bias	-0.9459					
	BW-W	Mu	-0.0448	-0.8583	-0.0384	1.9188	-3.4383	0.6626
		Sigma	0.0421	0.2199	0.2003	15.9371	7.4354	3.3386
		Beta	-0.5167	-6.2763	1.8261	-1.1138	-4.0411	2.5208
		Bias	-3.9796					
Left knee	LK-FF	Mu	-0.3078	0.7326	-0.3022	-1.5106	-1.4149	-8.4236
		Sigma	0.2220	0.1978	0.1159	5.1548	9.7167	16.3186
		Beta	2.3176	5.5042	-1.6811	0.9789	-0.1932	8.3310
		Bias	-8.6983					
	LK-FB	Mu	-0.3078	0.7326	-0.3022	-1.5106	-1.4149	-8.4236
		Sigma	0.2220	0.1978	0.1159	5.1548	9.7167	16.3186
		Beta	-1.5788	-5.0032	-3.5796	-0.3929	-0.2655	0.1731
		Bias	-0.8189					
	LK-W	Mu	-0.3078	0.7326	-0.3022	-1.5106	-1.4149	-8.4236
		Sigma	0.2220	0.1978	0.1159	5.1548	9.7167	16.3186
		Beta	-4.5751	5.5089	2.6828	-0.2400	0.9910	-2.0339
		Bias	-3.0821					

Left ankle	LA-FF	Mu	0.0173	0.7740	-0.2795	-0.2648	2.9662	-0.5372
		Sigma	0.2318	0.2025	0.1271	5.6352	14.0479	17.7340
		Beta	1.8583	2.4210	3.8863	0.4397	-1.9904	3.8782
		Bias	-1.7011					
	LA-FB	Mu	0.0173	0.7740	-0.2795	-0.2648	2.9662	-0.5372
		Sigma	0.2318	0.2025	0.1271	5.6352	14.0479	17.7340
		Beta	-0.7633	-1.0945	-1.5130	-0.5206	-1.1049	-0.7369
		Bias	-1.1714					
	LA-W	Mu	0.0173	0.7740	-0.2795	-0.2648	2.9662	-0.5372
		Sigma	0.2318	0.2025	0.1271	5.6352	14.0479	17.7340
		Beta	0.2729	1.4083	-0.3883	0.3845	2.0824	-0.9937
		Bias	-1.0295					
Right knee	RK-FF	Mu	-0.1862	-0.8615	-0.1601	-0.5131	-1.6077	-0.0099
		Sigma	0.2151	0.2133	0.0931	4.6363	6.9550	14.1699
		Beta	0.3322	-2.6013	2.6471	0.0815	-0.5773	-3.5969
		Bias	-2.5910					
	RK-FB	Mu	-0.1862	-0.8615	-0.1601	-0.5131	-1.6077	-0.0099
		Sigma	0.2151	0.2133	0.0931	4.6363	6.9550	14.1699
		Beta	-1.8511	-0.8453	1.9240	1.5161	0.2406	5.7929
		Bias	-1.3414					
	RK-W	Mu	-0.1862	-0.8615	-0.1601	-0.5131	-1.6077	-0.0099
		Sigma	0.2151	0.2133	0.0931	4.6363	6.9550	14.1699
		Beta	0.1272	-1.4768	-4.7429	-1.0990	0.9509	-0.3666
		Bias	-2.9143					
Right ankle	RA-FF	Mu	0.1440	-0.8083	-0.1975	2.7252	1.7660	-1.0574
		Sigma	0.2029	0.1930	0.2052	8.8196	8.2011	13.2323
		Beta	-4.3619	-4.1137	10.0344	-2.0457	0.3196	-5.6286
		Bias	-1.5800					
	RA-FB	Mu	0.1440	-0.8083	-0.1975	2.7252	1.7660	-1.0574
		Sigma	0.2029	0.1930	0.2052	8.8196	8.2011	13.2323
		Beta	-3.2400	-1.1731	1.4900	-0.0395	0.4945	4.4264
		Bias	-1.1882					
	RA-W	Mu	0.1440	-0.8083	-0.1975	2.7252	1.7660	-1.0574
		Sigma	0.2029	0.1930	0.2052	8.8196	8.2011	13.2323
		Beta	6.1496	2.2985	-12.2313	1.3856	-0.9670	-1.0440
		Bias	-3.9439					

Table 5- 1: Parameters of SVM Models of The Early-Fall Detection System

The confusion matrices of SVM models presented in the appendix A provided theoretical error in classification results. Since the sampling frequency has been set as 100Hz, these errors vary with the cut-off frequency. Table 5- 2 has shown the most ideal cut-off frequencies set for the 6 sensing units to minimize theoretical errors.

	Nape	Back waist	Left knee	Left ankle	Right knee	Right ankle
cut-off frequency	0.03 Hz	0.01 Hz	0.01 Hz	0.03 Hz	0.03 Hz	0.02 Hz
theoretical error	4.77%	1.80%	0.98%	16.64%	3.57%	0.54%

Table 5- 2: Cut-Off Frequency of Filters and Corresponding Model Error

The weight matrix in central control has been designed according to the results of receiver inspections in the appendix B. Table 5- 3 presents the weight matrix.

Activity	Nape	Back waist	Left knee	Left ankle	Right knee	Right ankle
FF	0	0.35	0.5	0.5	0.35	0.5
FB	0	0	0.5	0.5	0.5	0.5
W	0	0.5	0.5	0.35	0.35	0.35

Table 5- 3: Weight Matrix for Reports Analysis

The reports from the units were summed after being given particular weights. Three total points were then given and the maximum one that should also be above 1 would decide the output of the central control.

The stable window n has been set as 15 after balancing the sensitivity and accuracy of the activity classification.

5.3 Design of The Experiments

Three groups of experiments were designed for system verification of the completed early-fall detection system. Table 5- 4 listed the design of the experiments.

Experiment	Times	participant	Data record	The expectation of success result
Fall-forward detection	20	Qican Luo	Within 1000ms	Fall-forward detection reported within 500ms
Fall-backward detection	20	Qican Luo	Within 1000ms	Fall-backward detection reported within 500ms
Walk detection	20	Qican Luo	Within 5000ms	Walk detection remains in 5000ms

Table 5- 4: The Design of System Verification Experiments

Mean time to detect (MTTD), accuracy, true positive rate (TPR) and success rate were brought out after the experiments.

5.4 Experiment Results

Table 5- 5 presents the result of the full system test.

	MTTD	Accuracy	TPR	Success rate
Fall-forward detection	450 ms	100%	100%	90%
Fall-backward detection	485 ms	100%	100%	80%
Walk detection		100%	100%	100%

Table 5- 5: The Results of System Verification Experiments

Based on the experience that the general time a fall costs is 900ms [50], the average lead times before the impact of the system were calculated as 415ms and 450ms for fall backward and fall forward detection respectively.

Besides, the average detection time and accuracy of every unit have been recorded in Table 5- 6.

Activity types		Nape	Back waist	Left knee	Left ankle	Right knee	Right ankle
Fall forward	Time	216ms	850ms	308 ms	516ms	910ms	464ms
	Accuracy	0 %	100%	100%	100%	100%	100%
Fall backward	Time	150ms	558ms	518ms	530ms	628ms	543ms
	Accuracy	100 %	0%	100%	100%	100%	80%
Walk	Time						
	Accuracy	0 %	100%	20%	20%	100%	0%

Table 5- 6: The Performance of The Six Sensing Units

5.5 Result Analysis

The results of the experiments have proved that the early-fall detection system has realized its function in high accuracy of fall detection and classification and an acceptable success rate. The system has reached an accuracy of 100% in fall detection within 1000ms and walk detection within 5000ms. The fall-forward detection of the system has reached a success rate of 90% in reporting correct detection results within 500ms and the average time spent is 440 ms. The fall backward detection has a lower success rate of 80% and spends an average time of 493 ms for detection. The results also suggest that although the system can always achieve correct classification, the detection speed should be further improved. To obtain more accurate results for system evaluation, more experiments should be performed.

The error of the experiment was mainly caused by the fact that falls were performed after the participant observed the start of data collection. Since the human reaction time is about 200 ms [51], it can be considered that the system designed in this project has met the requirement according to the current results.

5.6 Discussion

Above all, the system developed in this report has realized the design and achieved the expectation of its function as well as accuracy. A comparison between this system and existing studies should be made for further verification of the system's rationality. Besides, two discoveries that are different from previous cognition have been found and should be discussed.

The following form shows the performance comparison between this system and some recent studies.

	Y.F. Wu et al. [52]	F. A. S. Ferreira de Sousa et al. [53]	N. Otanasap et al. [54]	S.M Shan et al. [55]	This study
Sensor	MEMS IMU: Front waist, Right thigh	MEMS IMU: Front waist	MEMS IMU: Chest	MEMS IMU: Back waist	MEMS IMU: Nape,Back waist, Lateral knees, Lateral ankles
Algorithm	Fisher linear discriminant analysis	Threshold Model	Dynamic Threshold Model	Support Vector Machine	Support Vector Machine
Data resource	Experiments	Experiments, Database	Experiments	Experiments	Experiments
Lead time	376ms- 404ms	259ms	365.12ms	203.59ms	415ms- 450ms
Accuracy	96.9%	95.86%	97.40%	100%	100%

Table 5- 7: Systems Comparison

In Table 5- 7, the system in this study used the most IMU sensors and has achieved the longest lead time, 415ms- 450ms, which is longer than that of the system developed by Y.F. Wu et al. which has a lead time of 376ms - 404ms. The accuracy rate of this system has achieved 100%, which is the same as the system by S.M Shan et al. which also used SVM. Like most studies, this study did not introduce any database as a data resource. However, the number of experiments in this study is less than that of others so as the types of activities included in the experiments. Therefore, The performance of this system needs to be further verified and evaluated.

For most of the studies above, the waist is the chosen place for setting IMU sensor. The lower limb sensor has been seen in the system by Y.F. Wu et al. and its value has been proved by the second-best lead time among the studies. Nape is the place that has only been chosen by this study according to the suggestion by G.Y. Shi et al. who considered that the head and the neck are the second choices except for the waist. However, the result has proved that neck is not an ideal location for fall detection in real life because its frequent movement can affect the detection of IMU seriously.

By comparison, the system's advantages of high accuracy and speed have been proved. Besides, the nape sensor should be replaced or removed in further study.

Through the method of human experiments that can reflect the natural reaction of the human body, two valuable facts have been found and should be discussed.

Firstly, sensors at different locations have different sensitivity and accuracy in detecting different activities. The confidence rank of sensors toward three activities is listed below.

Fall-forward:Left-knee > Left-ankle = Right-ankle > Back-waist > Right-knee >> Nape (0)

Fall-backward:Left-knee=Left-ankle > Right-ankle > Right-knee >> Back-waist = Nape (0)

Walk: Back-waist = Right-knee >> Left-knee = Left-ankle > Right-ankle = Nape (0)

According to experiments performed, the nape unit failed to contribute to any classification because it stayed reporting fall-forward detection after initiated and couldn't be improved by hardware replacement and model retraining. The back waist unit remained stable classification result during walking but couldn't clarify fall forward and fall backward. Sensors on the left leg responded to fall faster than that on the right leg. Sensors on lower limbs performed badly during the walking process except for the right knee unit which was as stable as the back waist unit. The weight matrix was designed according to this rank. The result of the full system test proved that sensors that have complementary advantages can detect and classify activities better after being given appropriate weights and working together.

Secondly, as the confidence rank shows, the accuracy and sensitivity of sensors on the left leg and right leg were not symmetrically similar. As the wearable IMU reflect the very detail of activities, the participant's personal habits including gait and the way of response to falls might be the cause of this result, suggesting that the confidence rank and ideal weight matrix may be different for different users. It can be inferred that the system with customized parameters is the most effective system for the particular user. This inference should be further studied with more participants.

Charpter 6 - Conclusion

6.1 Achievement

1. A wireless, wearable early-fall detection and classification system has been developed with high accuracy and speed of activity classification.
2. A reproducible parameters design process for the system has been developed and introduced in detail.
3. An environment for this study, including hardware and software, has been developed for further research and experiments.
4. A discovery of the fact that the accuracy and sensitivity of an IMU sensor for fall detection are affected by locations, types of falls and users' activity habits.

6.2 Discussion

The purpose of this project is to design a wearable smart sensing system for early-fall detection. The sensor used in this system is MEMS IMU and the algorithm for activities classification is ECOC-SVM.

A multi-IMU detection method has been applied to the project. The system is built by six sensing units and a central control supported by Matlab based on a PC. Sensing units classified data separately and reported results to central control for further analysis with a weight matrix before the final classification result was given according to the result of confidence comparison. The communication between sensing units and PC was realized by BLE. The cost of the design has been reasonable for home use while ethical approval has been fully considered.

The human experiment results of the system prove that the development of the system was successful. The system can classify fall forward and fall backward from walks within 500ms after falls begin with an average success rate of 85% while the accuracy of detection within 1000ms has reached 100%. The performance of this system proves that the joint use of multiple IMU sensors with appropriate weight is an ideal method to improve the speed and accuracy of fall detection.

During the development and verification process, it has been found that sensors in different locations classify different activities with different accuracy and sensitivity. Another discovery, the asymmetrical performance of lower limb sensors showed that sensors' performance may be affected by personal habits of activities, suggesting that weight matrix and other parameters should be customized design for users.

The system and the development process in this report have limitations. Because of the potential risk and requirements for skills of performing falls as well as self-protection, it is hard to recruit more participants. Due to the limitations of the number of samples, experimental methods and times, the effectiveness of the system needs further verification. Finally, only three activities can be classified by this system. Further function expansion is in great need.

6.3 Conclusion

A wireless, wearable early-fall detection system for home use has been developed successfully. The results of human experiments have proved that the system has achieved expectations of activity classification.

Two important findings were obtained. Firstly, sensors at different locations have different sensitivity and accuracy in detecting different activities. Secondly, the accuracy and sensitivity of sensors may be affected by users' habits of activities.

6.4 Future Work

In future studies, more types of falls and ADL will be included and trained.

The positions of the sensing units will be further evaluated. The central control should be developed into an APP supported by smartphones so the whole system can be wearable and free from signal interference from the environment.

An automatic parameters design system should be developed. With IMU data collected from the particular user, the system should be able to design the optimal parameters for each sensing unit and central control automatically.

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Appendix

Appendix-A: Confusion matrices of SVM classifiers of six sensing units

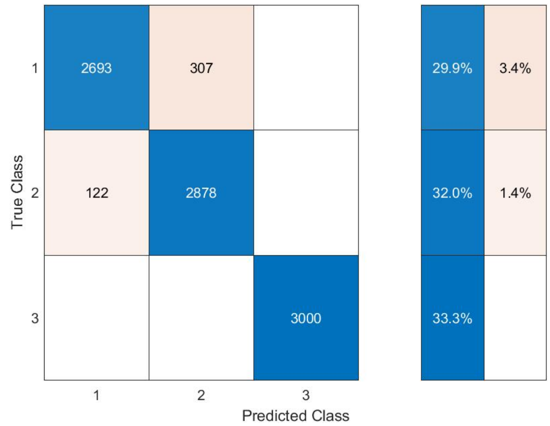

Figure. Neck classifier confusion matrix

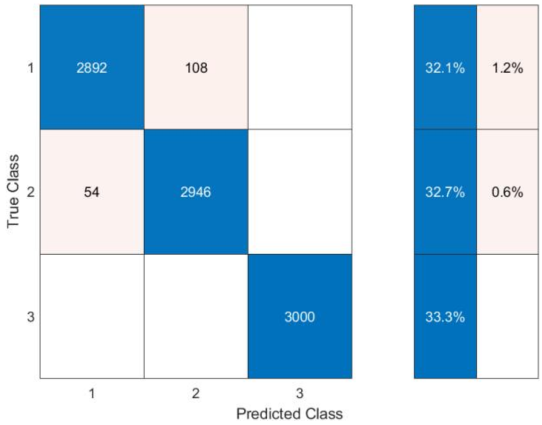

Figure. Back waist classifier confusion matrix

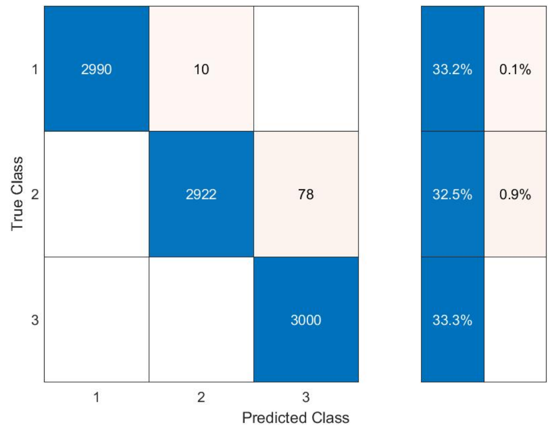

Figure. Left knee classifier confusion matrix

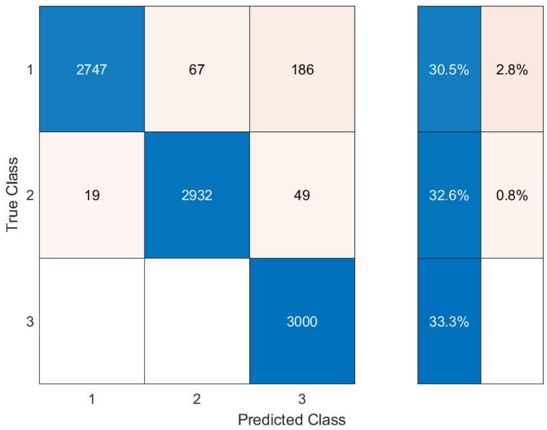

Figure. Right knee classifier confusion matrix

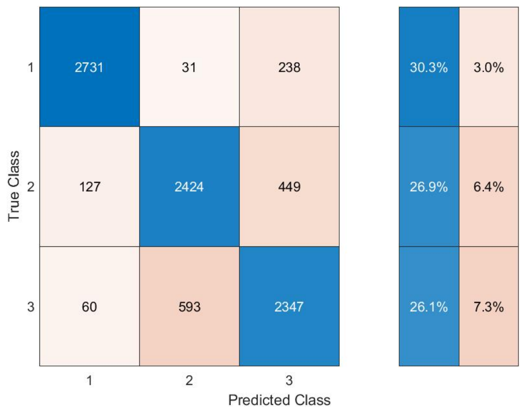

Figure. Left ankle classifier confusion matrix

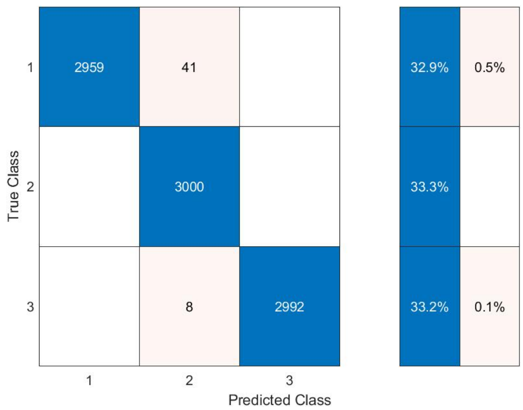

Figure. Right ankle classifier confusion matrix

Appendix-B: 2000ms results of the six units from three activities

B.1 Results of fall forward experiments

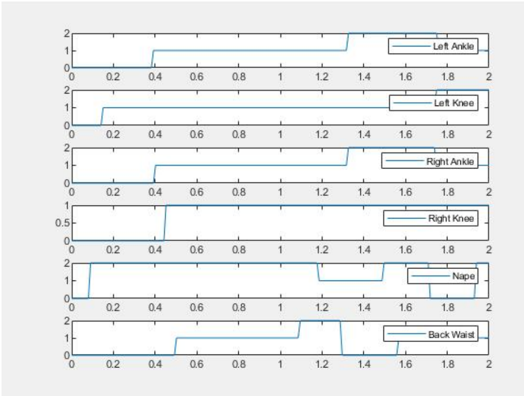

Figure. Fall forward experiment 1

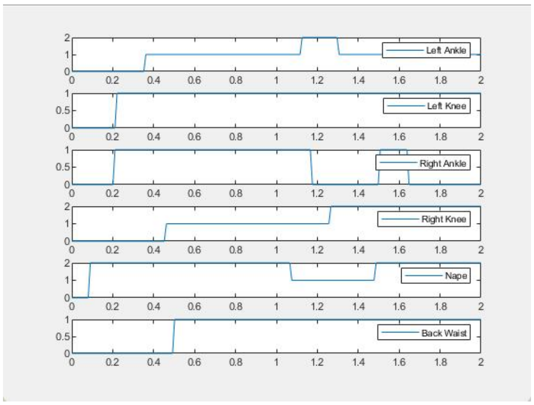

Figure. Fall forward experiment 2

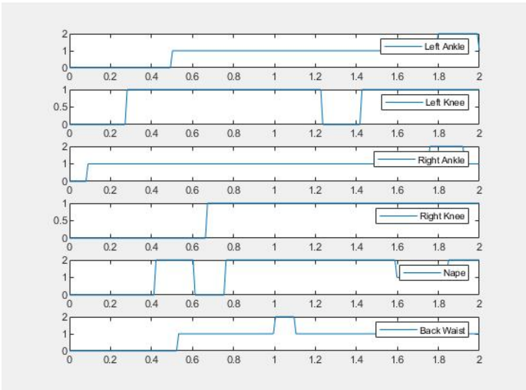

Figure. Fall forward experiment 3

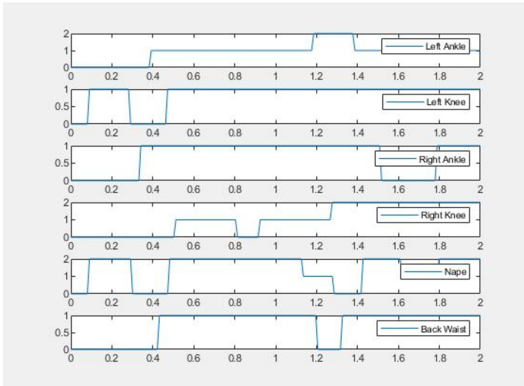

Figure. Fall forward experiment 4

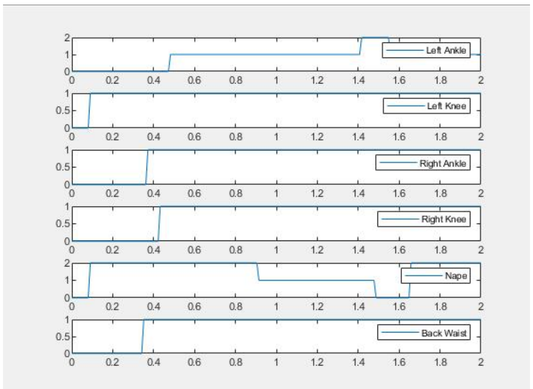

Figure. Fall forward experiment 5

B.2 Results of fall backward experiments

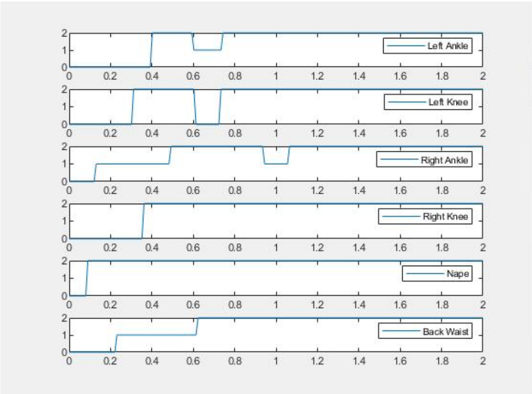

Figure. Fall backward experiment 1

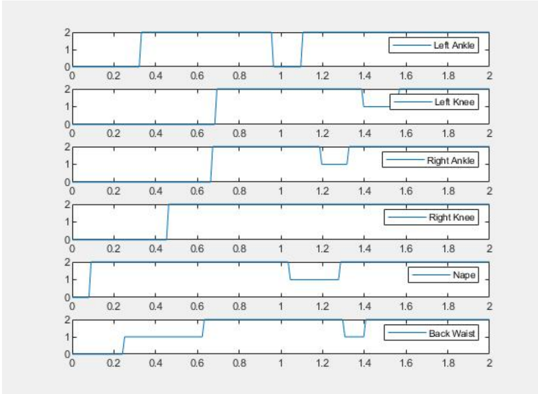

Figure. Fall backward experiment 2

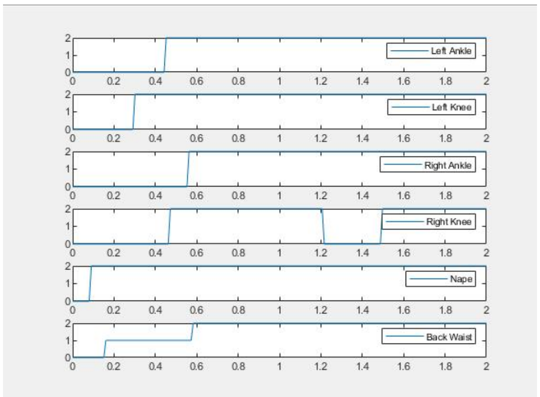

Figure. Fall backward experiment 3

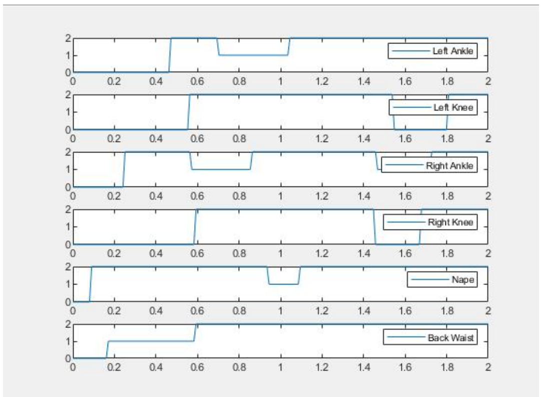

Figure. Fall backward experiment 4

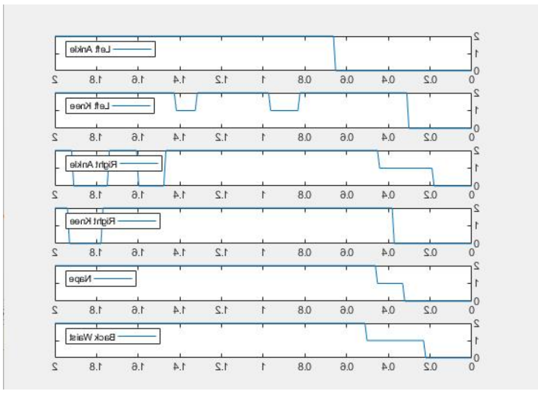

Figure. Fall backward experiment 5

B.3 Results of walk experiments

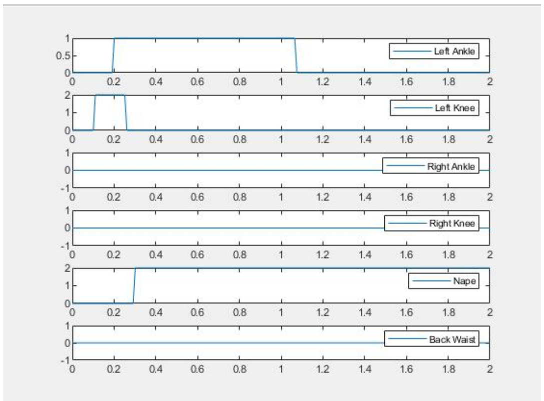

Figure. Walk experiment 1

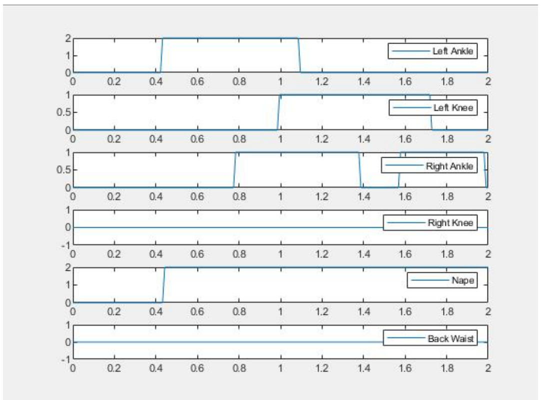

Figure. Walk experiment 2

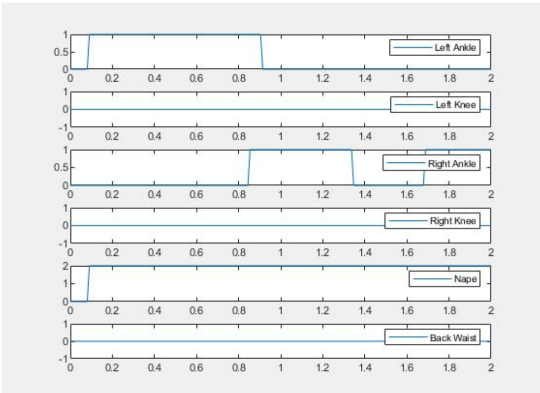

Figure. Walk experiment 3

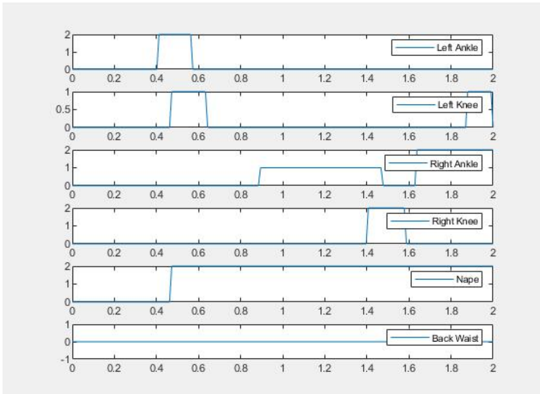

Figure. Walk experiment 4

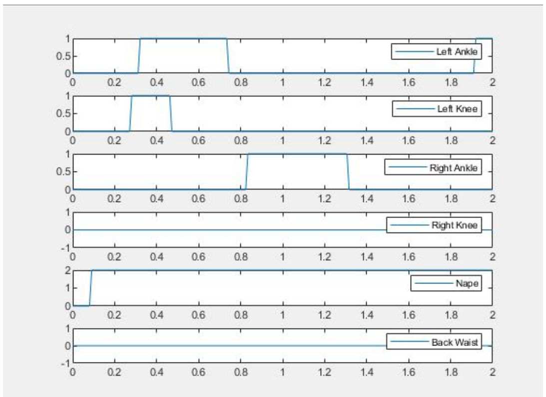

Figure. Walk experiment 5