HANDWRITING ANALYSIS USING IMU FOR SMALL HANDWRITING SIZE

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I hereby declare that this report title "*Handwriting Analysis Using IMU For Small Handwriting Size*" is the results of my own research except as cited in the references. The report has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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Date : JUNE 01, 2017

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Date : JUNE 01, 2017

This project and research work is dedicated to my beloved parents for their devoted caring throughout my life, my family who give the inspiration to me, my supervisor who always guide me in completing this project and also my friends for all their encouragement. Without their support this report may not have been done.

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ABSTRACT

Handwritten character recognition is one of the example of constant development of computer tools leads to a requirement of easier interfaces between man and the computer. Handwritten character recognition is one of the computer's ability where it can receive and interpret the handwritten input data from source as the document and also can transform it to machine readable and editable format. In this project the system was implemented using MATLAB software tools. There are several steps involved in this system including feature generation, feature selection and extraction and data classification. In signal preprocessing, there are some procedures involved which are calibration, filtering and normalization. During the preprocessing phase, the errors are filtered. During the feature generation phase, some formulas involved to process the acceleration include mean and root mean square (RMS). The purpose of feature selection and extraction is to increase the accuracy of the classification. Artificial Neural Network is recommended as the classifier for handwritten digit and hand gesture recognition in this project. Neural Network can make classification decision accurately and has advantage in high speed of learning. After completing the feature generation phase, the data classification process will take place and the extracted handwriting character will be classified. By applying the equation of mean, alphabet 'i' shows the highest accuracy which is 96.71% followed by alphabet 'u' that has accuracy of 90.71%. Alphabets 'a', 'e' and 'o' have almost same accuracy which are 82.81%, 83.72% and 85.13%. The accuracy depends on the acceleration and the hand gesture of the writing. After implementing the neural network, the overall performance of the digital pen achieved is 57%.

ABSTRAK

Pengenalpastian aksara/watak tulisan tangan adalah salah satu contoh pembangunan yang berterusan peralatan komputer yang membawa kepada keperluan antara manusia dan komputer. Pengenalpastian aksara tulisan tangan adalah salah satu keupayaan komputer di mana ia boleh menerima dan mentafsir data tulisan tangan dari pelbagai sumber sebagai dokumen dan juga boleh mengubah tulisan tangan kepada format yang boleh dibaca dan di sunting. Dalam projek ini, sistem dilaksanakan menggunakan perisian MATLAB. Terdapat beberapa langkah yang terlibat dalam sistem ini termasuklah pemilihan ciri dan pengektrakan ciri serta klasifikasi data. Dalam fasa pra-pemprosesan isyarat, terdapat beberapa langkah terlibat seperti penentukuran, penapisan aksara dan pemulihan aksara. Semasa fasa pra pemprosesan, kesilapan akan ditapis. Semasa fasa generasi ciri, beberapa formula terlibat dalam proses pecutan termasuk min dan punca min kuasa dua (RMS). Tujuan pemilihan ciri dan pengekstrakan adalah untuk meningkatkan ketepatan klasifikasi. Rangkaian neural amat disyorkan sebagai pengelasan tulisan tangan dan pengiktirafan tulisan tangan dalam projek ini. Rangkaian neural boleh membuat klasifikasi keputusan yang tepat. Selepas menamatkan fasa generasi ciri, proses pengelasan data akan berlaku dan watak tulisan tangan yang diekstrak akan diklasifikasikan. Dengan mengguanakan persamaan min dan sisihan piawai, 'i' menunjukkan ketepatan tertinggi iaitu 96.71% diikuti dengan 'u' yang mempunyai ketepatan sebanyak 90.71%. 'a', 'e' dan 'o' mempunyai ketepatan yang hamper sama iaitu 82.81%, 83.72% dan 85.13%. Ketepatan ini bergantung kepada halaju dan pergerakan tangan ketika menulis. Selepas menggunakan rangkaian neural, prestasi keseluruhan pen digital yang dicapai ialah 57%.

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LIST OF ABBREVIATIONS

IMU	-	Inertial Measurement Unit
MEMS	-	Micro Electro Mechanical System
LDA	-	Linear Discriminant Analysis
PNN	-	Probabilistic Neural Network
ANN	-	Artificial Neural Network
KBSC	-	Kernel-Based Class Separability
DTW	-	Dynamic Time Warping
DNN	-	Deep Neural Network
HMMs	-	Hidden Markov Models
PCA	-	Principal Component Analysis
FLD	-	Fisher's Linear Discriminant
ROC	-	Receiver Operating Characteristics
GUI	-	Graphical User Interface
STD	-	Standard Deviation
RMS	-	Root Mean Square

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CHAPTER 1

INTRODUCTION

1.1 Motivation

Knowledge discovery in database is an interactive and iterative process involve several steps such as selection, pre-processing, data classification and data analysis. Knowledge in data is very important as the knowledge will help to identify and interpret data which can be used later in future. For the example, knowledge discovery in database can be apply in interpreting the population data, classify the type of disease (medicine) and many more.

In March 2015, Minister of Lands, Housing and Urban Development of Uganda said, Uganda's urban population will increase from six million in 2013 to over 20 million in 2040. However, government having a problem in analyse the population data as majority of the population is concentrated on rural and urban areas only. So in this case, knowledge in discovery is important as this method can identify and interpret data of the population based on their area of living.

Besides, as reported by Health and Care Magazine, nearly 3000 cases per year involving brain tumors among the children. Among all the cases, nearly half of them are considered fatal. According to Director of brain research at Children's Memorial Hospital in Chicago (Health & Care, 20120, they have intention to create a database of gene of the patients in other to give them a better treatment. Therefore, they use knowledge discovery in database to classify the type of tumors.

In November 2002, former President of United States of America, President Bill Clinton spoke at Democratic Leadership Council [3], mentioned that after the event of 11 September 2001, the Federal Bureau of Investigation (FBI) has received a great amount of data considering five terrorist related to the incident. As stated from the data, one of the terrorist possessed 30 credit cards with some combined balances and stay in the country for almost 2 years. Moreover, President Bill Clinton concluded that further investigations are needed to gain some information for the data.

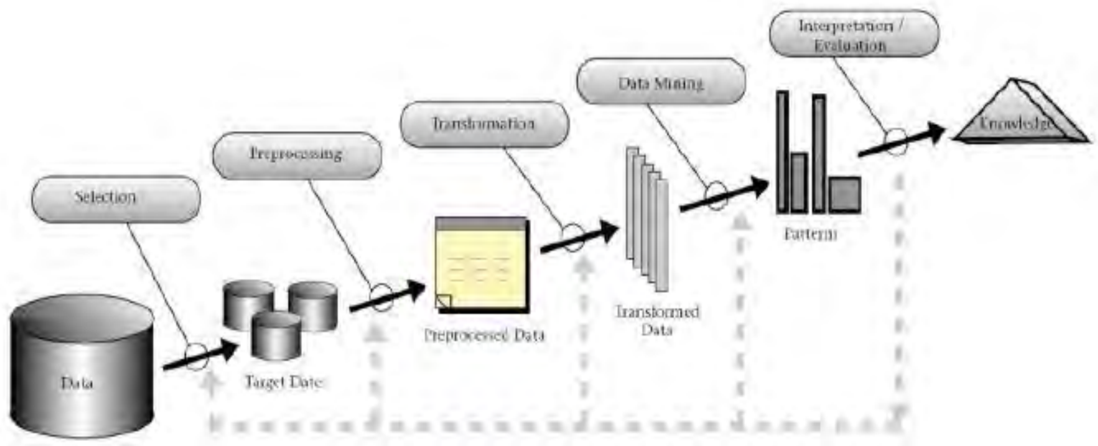

Figure 1.1: Steps in Knowledge Discovering of Database [22]

Handwriting analysis using IMU for small handwriting size will be focus in this project. Handwriting analysis is related to the knowledge discovery in database as the procedure in completing this project is quite similar with knowledge discovery in database. This project is aimed at developing a digital pen which will be helpful in recognizing small characters.

1.2 Problem Statement

Every aspect for the experiments such as sensor used, orientation of the hand gesture and acceleration that measured by accelerometer sensor have to be considered. The selection of the sensor is very important as it will be used to recognize desired command by hand motion to control the device. The mean and variance equation should be use in signal pre-processing as they are important features for handwriting recognition. These features are needed to simplify the raw data as many data are involved and the data have different range of value. Previous researchers have problem in selecting the most suitable method that need to be used to analyse the performance of digital pen for small handwriting. The acceleration of the hand gesture or hand motion also should be considered in conducting this project as this digital pen will be tested by some different users. The sensor will be placed on the digital pen in other to determine the orientation of hand gesture/motion of the users. We faced small problems in this task as some users are left-handed and some are right-handed. So, the users hand gesture orientation will be different.

1.3 Objective

The objectives of this project are:

1. To develop an experimental digital pen using IMU sensor which can recognize desired command by hand motion to control the device.
2. To extract important features from the sensor for the handwriting recognition.
3. To analyse the performance of the digital pen in term of small handwriting recognition.

1.4 Scope

In order to achieve the objectives above, some scopes have to be considered:

1. The device can be used to write digits or words on the paper in any orientation of hand gesture.
2. The analysis of this project would focus on five selected alphabets only based on the user's small handwriting to specify the performances of the device. The used of IMU sensor that consist of accelerometer and gyroscope would detect the trajectory and algorithm of the user's hand gesture.
3. The analysis of this project would focus on handwriting on flat surface only (paper) that has been specified into small size (5mm X 5mm).

CHAPTER 2

LITERATURE RIVIEW

In this chapter, another review will take part in order to complete the task given based on the previous research projects that are related to this project would be discussed. The perfect way to have a good explanation about this project is by exploring the facts related to this project in the internet, some reference books, a few of literature review on journal or patent about this project. Apart from that, this information will become additional sources to the project and can lead to successful project.

2.1 Project Background

A digital pen is a battery-operated writing device that allows the users to digitally capture a handwritten note or drawing by recognizing the hand gesture. Some of the digital pens come with handwriting recognition software that allows the users to import their handwritten notes into typed text. These pens do not require a docking station but instead send the captured notes directly to the user's PC or cell phone. In addition, the digital pen printing solution improves workflow, saving user's money, increasing data accuracy and security and making the operation more efficient than ever before [12]. Nowadays, digital pens come out in two different recognition features which is for 2D output and 3D output. Compared to conventional keyboard and touch-screen input methods, hand-writing character recognition in three-dimensional (3D) space using inertial sensors is an emerging technique. By using an inertial sensor-based device, users can freely write characters in 3D space [5].

2.2 Previous Research on Digital Pen for Handwriting Recognition

Wang et. al. [1] presents a handwritten character recognition system based on acceleration. The digital pen consists of an accelerometer sensor, a microcontroller and an RF wireless transmission module for sensing and collecting accelerations of handwriting and gesture trajectories. The character recognition system using a 3-dimentional (3D) accelerometer [1,3] includes the procedures of acceleration acquisition, signal processing, feature generation, feature selection and feature extraction. In signal processing, the accelerations are calibrated to remove the drift errors. The errors are then filtered via moving average filter and high-pass filter before entering the normalization process. Users can use the pen to write digits or characters and the accelerations of hand motions or hand orientation measured by the accelerometer which is wirelessly transmitted to a computer for online trajectory recognition.

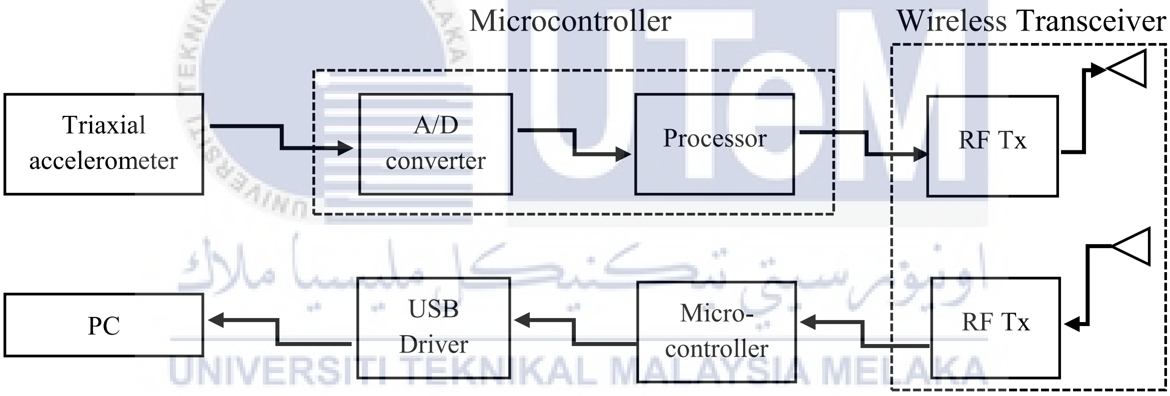

Figure 2.1: Schematic diagram of the digital pen module [1]

Meenaakumari et. al [2] presents an MEMS accelerometer sensor based on gesture recognition and its applications. The hardware module consists of a triaxial mems accelerometer, microcontroller and zigbee wireless transmission module for sensing and collecting accelerations of handwriting and hand gesture trajectories. The accelerometer is connected wirelessly to a personal computer for trajectory recognition. The character recognition procedures consist of information assortment collections and signal preprocessing for reconstructing the trajectories to remove the cumulative errors caused by drift of sensors. The author state that, by changing the position of MEMS, the users are able to show the alphabetical characters and numerical within the PC [2].

Motion sensor [1,3, 5,6,7] is a device which the accelerometer and gyroscope fused on a single chip together. Mirza et. al. [3] proposed a pen that employs its motion to transfer the writing into an editable word document by record the motion of the pen and applying a microcontroller for serial communication. The raw data from the motion sensors is converted to a processed useful data by implementing a number of error corrections. Once the motion is recorded, a specially designed algorithm defined briefly used to reconstruct the word. The well calibrated sensor produces the perfect results and help to achieve a greater reconstruction rate as output. The equation for displacement from acceleration as shown below [3]

$$X_{n+1} - X_n = \left[\frac{1}{2}a_{n+1} + \frac{3}{2}a_n + 2\sum_{j=1}^{n-1} a_j\right]\frac{t^2}{2} \qquad (1)$$

Deselaers et. al. [4] presents a trajectory of the phone's corner that is touching the writing or drawing surfaces. Gyropen is a method that give the same experiences to user as writing using a pen [4]. The angular trajectory is used in this reconstruction which removes the necessity for accurate absolute 3D position estimation, a task that can be difficult using low-cost accelerometer. The Gyropen is connected to a handwriting recognition system and perform two proof-of-concept experiments to demonstrate that the reconstruction accuracy of Gyropen is accurate enough to text entry.

Shashidhar et. al [5] presents a wireless-inertial-measurement-unit (WIMU) based hand motion analysis technique for handwriting recognition in three-dimensional (3D) space. The proposed handwriting recognition system is not bounded by any limitations or constraint; users have the freedom and flexibility to write characters in free space. It uses hand motion analysis to segment hand motion data from WIMU device that incorporates magnetic, angular rate, and gravity sensors (MARG) and a sensor fusion algorithm to automatically distinguish segments that represent handwriting from non-handwriting data in continuous hand motion data. Dynamic time warping (DTW) [5] recognition algorithm is used to recognize handwriting in real time. The users can freely write in air using an intuitive WIMU as an input and hand motion analysis device to recognize the handwriting in 3D space.

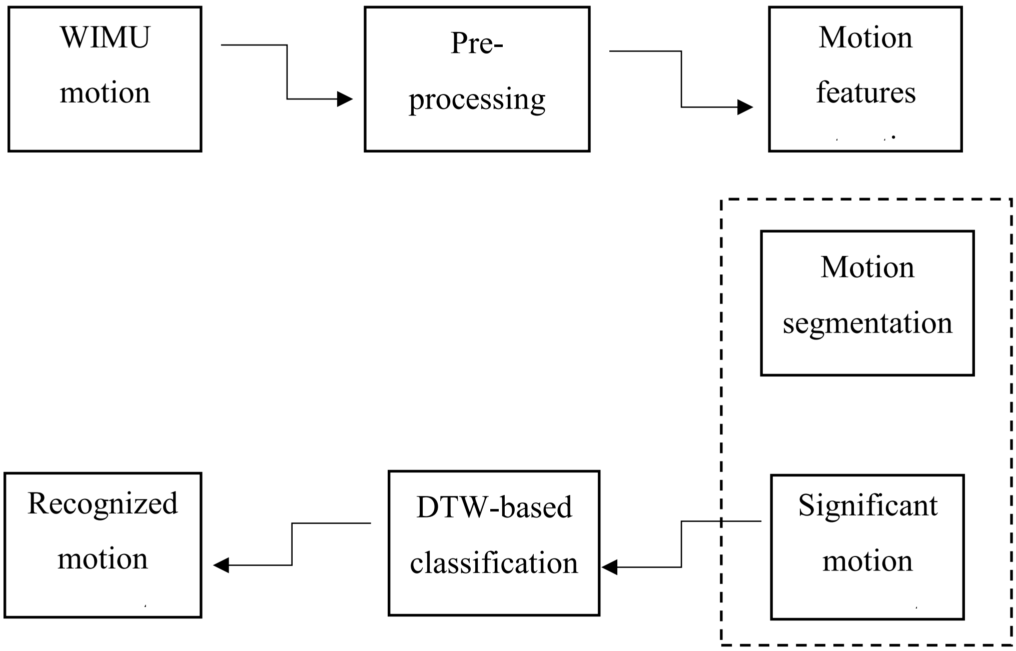

Figure 2.2: Handwriting segmentation and classification [5]

Li et. al [6] proposed a novel interactive method for recognizing handwritten words using the inertial sensor data available on smart watches. The goal is to allow the user to write with a finger and used the smart watch sensor signals to infer what user has written. Past work has exploited the similarity of handwriting recognition to speech recognition in order to deploy HMM based methods. In contrast to speech recognition, however in this scenario, the user can see individual letters that recognized on a sequential basis, and provide feedback or corrections after each letter. The researchers exploit these key difference to improve the input mechanism over a classical source-channel model. For a small increase in the amount of time required to input a word, they improve recognition accuracy from 59.6% to 91.4% with an implicit feedback mechanism and to 100% with an explicit feedback mechanism.

The digital pen [1,7] is a pen type portable device having inertial sensor example triaxial accelerometer for general motion sensing, that facilitates the users to interact with computer, Zigbee module used for wireless communication. Leena et. al. [7] presents an effective trajectory recognition algorithm that can efficiently select most significant features from the time and frequency domains of acceleration signals collected from inertial sensor and project the feature space into a smaller feature dimension for motion recognition with high recognition accuracy.

Georgi.M et. al. [8] evaluate the performance of a wearable gesture recognition system that captures arm, hand and finger motions by measuring movements and muscle activity at the forearm. The analyse the signals of an IMU worn at the wrist and the EMG of muscles in the forearm to infer hand and finger movements. A set of 12 gestures was defined based on their similarity to actual physical manipulations and to gestures known from the interaction with mobile devices. They recorded performances of the gestures set by five subjects in multiple sessions. Hidden Markov Models (HMMs) [8] is used as the classifiers. They achieve a recognition rate of 97.8% in session-independent and 74.3% in person-independent recognition.

The nature of handwritten characters, conversion of handwritten data into electronic data [9] usually black and white image file and neural network approach to make machine capable of recognizing hand written characters. Perwej et. al [9] developed a machine recognition of hand written character using neural network. In preprocessing phase, each character deals with technique for enhancing contrast, removing noise and isolating regions whose texture indicate a likelihood of character information. The picture classifier Principal component analysis (PCA) is used as a tool in exploratory data analysis and for making predictive models.

Milner.Ben [10] has developed a conventional tablet-based handwriting recognition which used a pair of accelerometers sensor as the device to measure the movement of the pen. The accelerometer package is produced by Analog Devices [20] with the accelerometer placed at the side of the pen. Sampling frequency of around 60Hz [10] is applied by the author as the sampling frequency must high enough to ensure the rapid acceleration can be accurately measured. Because of handwriting recognition and speech recognition have close similarity, it was decided to model the handwriting using Hidden Markov Models (HMM) as HMM is the technique that have been success in the speech recognition task.

Choi et. al. [11] presents a pen-style hardware for the recognition of handwritten characters. The hardware has a 3-dimentional acceleration sensor, an amplifier, a microcontroller with AD converter and communication port but does not need any touching screen. The algorithm procedures include the signal preprocessing, feature extraction and classifier. Both Hidden Markov Models (HMM) and Dynamic Time Warping (DTW) are used as the recognition classifier in this project [11]. The hardware and software for the experiment with 10 Arabic numerals show high recognition rates where 100% for the writer-dependent and 90.8% for writer-independent cases. This recognition rates clearly demonstrates that the usefulness of the acceleration-based handwritten character recognition system can work even without touching screen or pad.

End point detection is proposed for motion direction by acceleration [12]. Instead of the conventional methods based energy feature normalization in automatic speech recognition and threshold-based algorithms, supervised learning in pattern recognition is proposed in this task to discriminate a motion state and a non-motion state. The selected acceleration values based on correlation coefficient are used to form the feature vectors and then transformed 2D or 3D feature vectors into variants vectors with Principle component analysis and Fisher's Linear Discriminant (FLD). Apart from the various feature vectors, artificial neural network has been designed to analyse the feasibility of the proposed algorithm.

Dhivya et. al. [13] presents a pen like input device for computer using inertial sensor (MEMS). The device consists of triaxial accelerometer, an atmega8 microcontroller and a zigbee wireless transmission module. Based on inertial sensor this device can be used as a normal pen and the characters written by using this pen will be displayed in monitor. The accelerometer used in this device is function as the detector to measure the acceleration of the hand movement and recognize the hand gestures. The digital pen device can be used to write the hand digits or alphabets by the users. The signals from the accelerometer will be transmitted to the monitor with the help of Zigbee. The signals will be processed in the pc and the results will be displayed in monitor. Hence there is no need for keyboard typing which is quite difficult than normally writing by using a pen in a notebook.

Sanchez et. al. [14] proposed a system of on-line character analysis and recognition using fuzzy neural networks (FasArt). Two methods for segmenting handwritten components into strokes are proposed, with better experimental results for the method based on the biological models of handwriting in term of consistency. A systematic experimental study of different schemes is also described based on Shannon entropy and clustering maps. Lastly, the steps towards the construction of an allograph lexicon are shown that the generation of fuzzy-rules by FasArt architecture.

Priyanka.M et. al. [15] presents an electronic handwriting character recognition (E-HWCR) device. On-line handwriting character recognition using accelerometer is the basic proto-type for all the latest technologies. With the advancement of electronics, the different technologies used in computer vision helps to organize a hand written character more effectively and yields a reliable input [21]. In this project, the recognition process is done by using a micro-electromechanical device (MEMS) accelerometer and microcontroller within built ADC. The characters are stored using processor and it is interfaced to the computer for recognizing the data with any Integrated Development Interface (IDE) person's hand such as bio-metric technique works on accelerometers in built.

Pen with inbuilt inertial sensors are new input instruments which may be used as an alternative to keyboard [13]. Jahidabegum.K et. al. [16] developed a digital pen device for character recognition system for text entry using inertial sensor. Motion trajectory recognition is very challenging in this project because the different users have different speeds and style or orientations to write the character or make gesture. Character recognition accuracy depends on the features selection and classification technics. Accuracy is evaluated using two classification technic which are Simple PNN classifier and KNN classifier where KNN classifier gave better recognition accuracy rate than Simple PNN.

2.3 Comparison and summary of previous system of handwriting and pattern recognition device.

Table 2.1: Previous study systems comparison

Title	Input & Sensor	Signal Processing	Feature Extraction	Classifier	Recognition Rate (%)
Accelerometer-Based Digital Pen with a Trajectory Recognition Algorithm for Handwritten Digit and Gesture Recognition [1]	Acceleration & Accelerometer sensor	Calibration, high-pass filter, normalization	Linear Discriminant Analysis (LDA)	Probabilistic Neural Network (PNN)	98.0
MEMS Accelerometer Based Hand Gesture Recognition [2]	Acceleration & MEMs, Accelerometer sensor	Calibration, high-pass filter, normalization	Linear Discriminant Analysis (LDA)	Probabilistic Neural Network (PNN)	98.0
Application of Motion Sensors in Hand Writing Conversion [3]	Acceleration, tilt angle orientation & Motion sensor	Stemming, normalization, off-set reduction	Kernel-Based Class Separability (KBCS)	Kalman Filter	
Gyropen-Gyroscopes for Pen-Input with Mobile Phone [4]	Angular velocity, acceleration, magnetic field	Postprocessing, Calibration	Mean, variance, standard deviation		93.0

	& Motion, Orientation sensor				
Handwriting Recognition in Free Space using WIMU-Based Hand Motion Gesture [5]	Acceleration, angular velocity, magnetic signal & Motion, magnetometer sensor	Calibration, filters		Dynamic Time Warping (DTW)	99.5
Feedback-Based Handwriting Recognition from Inertial Sensor Data for Wearable Device [6]	Cartesian acceleration, angular velocity & Inertial sensor	Normalization, filters	Mean, variance, standard deviation	Deep Neural Network (DNN)	91.4
Digital Pen for Handwritten Digit and Gesture Recognition using Trajectory Recognition Algorithm Based on Triaxial Accelerometer [7]	Acceleration & MEMs sensor	Filtering, normalization	Kernel-Based Class Separability (KBCS)	Probabilistic Neural Network (PNN)	98.2

Recognizing Hand and Finger Gesture with IMU based Motion and EMG based Muscle Activity Sensing [8]	Acceleration, angular velocity, electrical signal & IMU, EMG sensor	Normalization		Hidden Markov Models (HMMs)	97.8
Machine Recognition of Hand Written Character using Neural Network [9]	Image & Vision sensor	Normalization, error removing	Characteristic Loci	Principal Component Analysis (PCA)	93.5
Handwriting Recognition using Acceleration-Based Motion Detection [10]	Acceleration & Accelerometer	Sampling, band-pass filter, down-sampling	Class-separability	Hidden Markov Models (HMM)	96.0
On-line Handwritten Character Recognition with 3D Accelerometer [11]	Acceleration & Accelerometer	Noise filtering, amplitude normalization, under-sampling	Principle Components Analysis (PCA)	Hidden Markov Models (HMM), Dynamic Time Warping (DTW)	100.0 90.8

Pattern Recognition-Based Real-time End Point Detection Specialized for Accelerometer Signal [12]	Acceleration, Angular velocity & IMU sensor	Normalization	Principle Components Analysis (PCA), Fisher's Linear Discriminant (FLD)	Artificial Neural Network (ANN)	
A Pen like Input Device for Computer Using Inertial Sensor [13]	Acceleration & Inertial sensor		Mean, variance		92.0
On-line Character Analysis and Recognition with Fuzzy Neural Network [14]		Noise filtering, segmentation	Shannon entropy, Clustering map	FasArt neuro-fuzzy Architecture	95.0
Electronic Handwriting Character Recognition (E-HWCR) [15]	Acceleration & MEMs, Accelerometer sensor	MATLAB tools -image processing -stroke recognition	Mean	Bio-metric methods	98.0
Character Recognition System for Text Entry using Inertial Pen [16]	Acceleration, angular velocity & Accelerometer, Gyroscope	MATLAB tool	Time domain mathematical, statistical metrics	PNN, K.Nearest Neighbor (KNN)	82.0

Feature Processing and Modelling for 6D Motion Gesture Recognition [17]	Acceleration, angular velocity, orientation. Image & IMU, Optical sensor	Normalization	Rubine's Feature	Hidden Markov Models (HMM), Statistical Feature-Based Linear	93.8
Handwritten Character Recognition using Orientation Quantization Based on 3D Accelerometer [18]	Acceleration & Motion sensor	Filtering, normalization		Hidden Markov Models (HMM)	94.29
Magic Wand: A Hand-Drawn Gesture Input Device in 3D Space with Inertial Sensor [19]	Acceleration, angular velocity & Inertial sensor	Stroke segmentation, noise filtering	Mean, variance	Bayesian Network	99.2

2.4 Conclusion on Previous Research

Based on previous literature above, the best variable for digital pen device is acceleration as most of the researchers set the acceleration as their input. Instead of the acceleration, [5, 17, 19] researchers set the angular velocity and magnetic signal as the input. Besides, most of the projects used motion sensor (accelerometer and gyroscope) as motion sensor has high ability in recognize the motion of hand gesture. By using motion sensor, the position, acceleration and orientation of hand gestures can be obtained smoothly. Some projects also used EMG sensor as they extract the angular velocity and electrical signal from muscle activities. Most of the projects use neural network as the classifier to classify the handwriting and analyse the performance of the digital pen. Hidden Markov Models (HMMs) also known as a good classifier among the previous research projects.

By referring the previous research, the motion sensor (IMU) is selected to be use for this project as motion sensor play the best role in recognizing the motion. The mean and variance equations are selected as they are the important features for handwriting recognition. These features are need to simplify the raw data as many data are involved and the data have different range of value. The use of neural network as the classifier in this project is recommended as most of the literature state that the neural network acted as the best classifier for digital pen project. Neural Network can make classification decision accurately and has advantage in high speed of learning.

CHAPTER 3

METHODOLOGY

In this chapter, the methodology to achieve the objectives of the project is discussed. This chapter covered the method used in developing a portable digital pen by using IMU sensor and analyse the performance of the portable digital pen. Figure 3.1 below shows the overview methodology of trajectory recognition algorithm steps in achieving the objectives of this project.

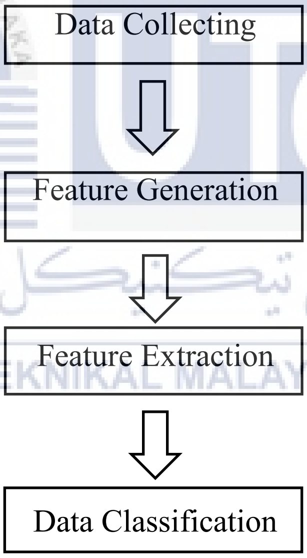

Figure 3.1: Steps for Trajectory Recognition Algorithm

3.1 Hardware Architecture

3.1.1 Hardware Connection

The idea of this project is to develop an experimental digital pen using Inertial-Movement-Unit (IMU) that can recognize desired command by hand motion to control the device without any limitations. In other to achieve this objective, a hardware consist of some components is created.

Figure 3.2: Digital Pen Hardware Connection.

As shown in Figure 3.2 above, the Inertial Measurement Unit (IMU) was connected to the Arduino kit. The IMU will determine the position and motion of the hand gesture or handwriting orientation of the users once they used the digital pen. The data from the IMU will be sending to Arduino kit and the Arduino will convert the data to a signal that will be transmitted via connecter wire. The second connecter (USB) that acts as a receiver will receives the signal from the transmitter and interface the data to the software. The proposed of trajectory algorithm consisting of acceleration, feature generation, feature selection and extraction.

Figure 3.3: Block diagram of digital pen.

Arduino is a microcontroller based-kits that is an open-source prototyping platform based on easy-to-use hardware and software. Arduino Nano is different from other types of Arduino board as it lacks of DC power jack and operates with Mini-B USB cable. Arduino Nano also smaller in size compared to other type of Arduino boards which make it able to use in simple hardware. Arduino Nano can be programmed by using C language via Arduino Software [23]. Accelerometer sensor is a motion sensor that will recognized the gesture and measured the acceleration of the gesture.

3.1.2 MATLAB Software

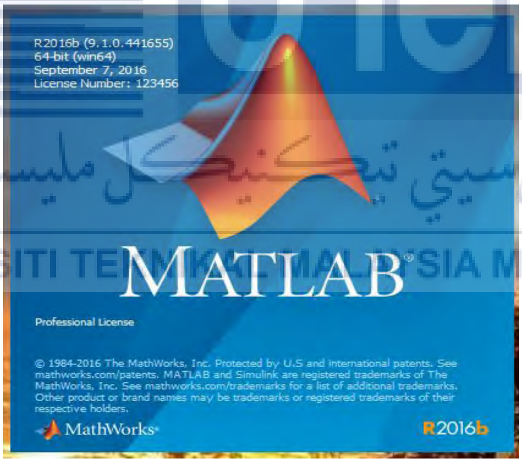

Figure 3.4: MATLAB Software

MATLAB is a high performance language for technical computing. It integrates computation, visualization and programming in easy-to-use environment where problems and solutions are expressed in mathematical rotation.

3.2 Methodology to achieve the objectives

3.2.1 Early calibration of MPU6050

MPU6050 is a sensor that has six degrees of freedom and suitable to use for motion detection. Before it is implemented to some task, MPU6050 should be calibrated first to ensure the accuracy of MPU6050 is accurate.

3.2.2 Procedure of Trajectory Algorithm

i. Feature Generation (Selection and Extraction)

This features of pre-processed acceleration include mean and VAR.

a. Mean: mean value of the acceleration of each hand gesture

$$Mean = \frac{1}{|W|} \sum_{i=1}^{|W|} x_i \tag{1}$$

b. VAR

$$VAR = \frac{1}{|W|-1} \sum_{i=1}^{|W|} (x_i - m)^2 \tag{2}$$

The purpose of feature selection and extraction is to increase the accuracy of the classification. For the pattern recognition, Linear Discriminant Analysis (LDA) is an effective feature extraction which use a linear transformation.

ii. Data Classification

Neural Network is recommended as the classifier for handwritten digit and hand gesture recognition in this project. Neural Network can make classification decision accurately and has advantage in high speed of learning.

3.3 Data Classification using Neural Network

Neural Network is a process of information based on biological nervous system such as brain process. The structure of the information processing system is the most important key element of this network. A Neural Network is used for configuration for a specific application such as pattern recognition or data classification based on a learning process. Neural network is very important in stock market prediction as the business of stock market has become more complicated year to year. Neural network can be used to predict stock prices in short time as it can verify a lot of information quickly [10].

Neural network comes in some advantages such as can create its own organisation of the information received during the learning time. This network also has high ability in learning on how to do tasks based on the data given for training in real time operation. The computations may be carried out in parallel and hardware devices will be designed. The agency that run some manufacturing processes can take advantages on this ability for future work. The basic type of neural network is known as the back propagation neural network (BPN). The back propagation means the system need to send the error (mistakes made by the network during training) backwards in order to teach the network the right and wrong cases [9]. Figure 3.7 below show the connection of the neural network. Neural networks are organized in layers where the layers are made up of a number of nodes which contain some functions for activation. The input layer will represent the patterns which will connected to hidden layers. The hidden layers then link to output layer to produce output layer.

Other type of neural network is named as Artificial Neural Network (ANN). This network can be made in many different ways and can try to copy the brain in many ways. Artificial neural network is not intelligent but it can be the best network for recognizing patterns and making the complex problems become simple form and good at generalizing from a set of training data [9]. There are two Artificial Network topologies which are feedforward and feedback. The information of feedforward ANN flow in unidirectional and do not have feedback loops. A unit sends information to other unit where this unit do not receive any information yet. Basically. This type of ANN is used in pattern recognition, generation and classification. For feedback ANN, feedback loops are allowed and this type of ANN is very suitable to use in content addressable memories.

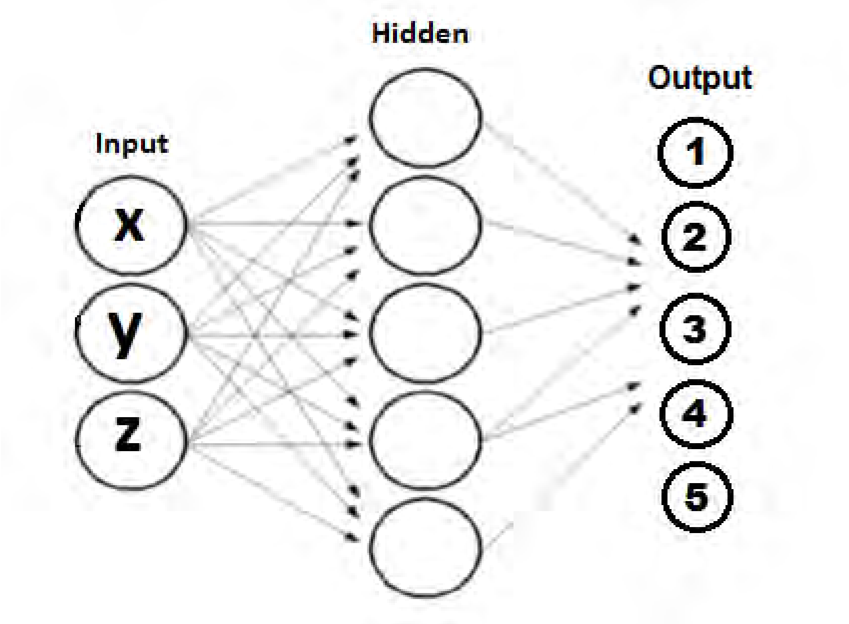

Figure 3.5: Structure of Neural Network for data classification.

As shown in Figure 3.5 above, the structure of neural network for data classification consist of three layers which are input layer, hidden layer and output layer. The input layer represents the patterns which will connected to the hidden layer. For this project, input layer will be fed up with three inputs which are data for x-axes, y-axes and z-axes for each alphabet. The number of neurons in the hidden layer were set up for 25 neurons. The hidden layers then link to output layer to produce the outputs. Five outputs have been set up that represent the class of the selected alphabets. Output 1, 2, 3, 4 and 5 represent the class of alphabets ‘a', ‘e’, ‘i’, ‘o’ and ‘u’ respectively.

3.4 Performance Measurement (ROC)

In the performance measurement, ROC is used to do the hypothesis of the data. *ROC* is known as receiver operating characteristics is a technique use for visualizing, organization and selecting classifications based on their performance. ROC graphs commonly used in medical decision making and nowadays it have been used in machine learning and data mining research.

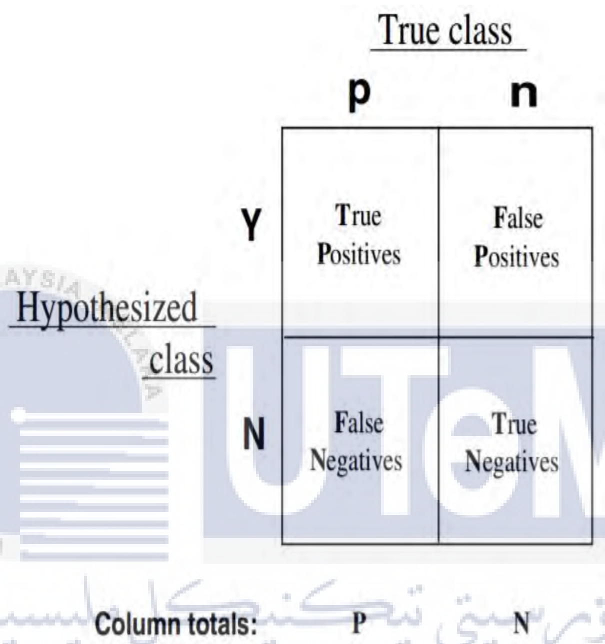

Figure 3.6: Confusion matrix and common performance metrics calculated from it [16]

Figure 3.6 shows a confusion matrix and equations for calculate the common metrics. The errors are represented by the numbers of the diagonal. The *true positive rate* and *false positive rate* of a classifier are simplified as

$$tp\ rate = \frac{Positives\ correctly\ classified}{\text{Total positives}} = \frac{TP}{P} \tag{3.4}$$

$$fp\ rate = \frac{Negatives\ correctly\ classified}{\text{Total negatives}} = \frac{FP}{N} \tag{3.5}$$

The equations to calculate the common performance metrics as shown below:

$$precision = \frac{TP}{TP + FP} \qquad (3.6)$$

$$accuracy = \frac{TP + TN}{P + N} \qquad (3.7)$$

tp rate will be plotted on the Y axis while *fp rate* plotted on the X axis. A ROC graph usually plotted between benefits (true positives) and costs (false positives) as shown in Figure 3.7.

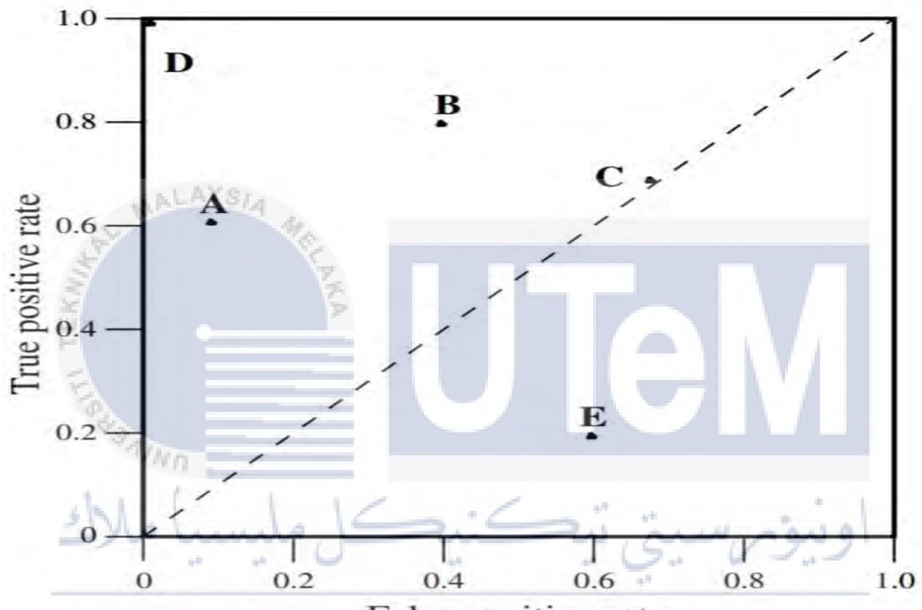

Figure 3.7: A basic ROC curve [16]

3.5 Environmental Set Up for Acceleration Data

The experimental portable device consists of the motion detection module which is able to record the motion of the pen while the user writes. The IC chosen was MPU 6050 which is based on Inertial-Measurement-Unit (IMU) technology. The motion sensor is GY-521 board that has an accelerometer in it which will record the movement of the pen and hand gesture using the orientation degree and acceleration. The raw data gathered and then converted to acceleration and rotation motion using the formulae. This data is in the form of motion waveforms which will be processed by error correction. The axis used were x-axis as the input data and y-axis used to record the movement of the pen resulting from the user's motion. The orientation angle and acceleration obtained from the motion detection of the device provide the information that will help to plot the data.

Figure 3.8: Gesture Recognition System.

NAME: GENDER: Male / Female

AGE : HANDWRITING: Left / Right

1. Alphabet ‘**a**’

☐ ☐ ☐ ☐ ☐

2. Alphabet ‘**e**’

☐ ☐ ☐ ☐ ☐

3. Alphabet ‘**i**’

☐ ☐ ☐ ☐ ☐

4. Alphabet ‘**o**’

☐ ☐ ☐ ☐ ☐

5. Alphabet ‘**u**’

☐ ☐ ☐ ☐ ☐

Figure 3.9: Plain paper with small boxes (5mm X 5mm).

3.6 Experimental Set up

The algorithm was designed to convert the data receive by accelerometer into a recognizable letter on a screen. The data will be transferred into feature extraction to reduce the error reading and noise. The data then fed up into a neural network classifier to recognize the motion to which feature it belongs.

During data collection phase, twenty students (ten males and ten females) ages between 19 to 24 years old were selected to participate in this experiment. Since the accelerometer sensor used will work on acceleration of the hand gesture, the different gender of participants was needed as the male and female participants will produce different acceleration during the writing process. Each participant was asked to hold the pen and draw the selected alphabets (five) and the pen tip must touch the plain paper provided. Each participant was given same size and type of plain paper in order to avoid some error that may cause by the surface of the paper. The spacing between participant's hand and the accelerometer sensor on the pen was set about ±5cm as the sensor may cause some negative effects to the participants.

20 candidate X 5 alphabets 5 times = 500 data

60% data → Training

20% data → Test

The candidates need to write the five selected alphabets (a, e, i, o, u), five times for every alphabet.

The candidate's category is stated as below:

Table 3.1: Category of the candidate

NO	NAME	GENDER	AGE	WRITING
1	Muhammad Azreen Syamil B. Azhar	Male	23	Right-Handed
2	Muhammas Amir Afiq Bin Suhaimi	Male	23	Right-Handed
3	Abang Ahmad Afiq	Male	23	Right-Handed
4	Mohd Hanis Bin Norman	Male	23	Right-Handed
5	Nabilfikri	Male	23	Right-Handed
6	Siti Norbaizura Binti Abdul Aziz	Female	23	Right-Handed
7	Nur Athirah Hazwani Binti Abdul Manaf	Female	22	Right-Handed
8	Nur Iffah Binti Ibrahim	Female	22	Right-Handed
9	Aika An Najwa Binti Mohd Marzudin	Female	23	Right-Handed
10	Maziah	Female	23	Right-Handed
11	Muhammad Al Akeef Bin Al Amin	Male	24	Left-Handed
12	Anuar Burhanie Bin Burhan	Male	24	Left-Handed
13	Ikmal Farez	Male	23	Left-Handed
14	Haiziel Aimin	Male	21	Left-Handed
15	Adib Azman	Male	21	Left-Handed
16	Nur Aqeelah Binti Napis	Female	22	Left-Handed
17	Hasrin Nadia Binti Alias	Female	21	Left-Handed
18	Intan Nurhafizah	Female	20	Left-Handed
19	Farahanie Binti Bazarudin	Female	23	Left-Handed
20	Lorizka Xalfina	Female	24	Left-Handed

CHAPTER 4

RESULT AND DISCUSSION

This chapter discussed about the results collected from the experiment that has been done in completing and achieving the objectives stated in chapter one.

4.1 Result from Handwriting Construction

4.1.1 Raw Data Captured from Candidate

Raw data of hand gesture from IMU sensor were collected via Arduino software. The analysis was done to analyze the data that representing the handwriting activities. The data were collected from the hardware where a subject was asked to write the selected five alphabets ‘a’ ‘e’ ‘i’ ‘o’ ‘u’ on a plain paper that has been classified into small size (5mm x 5mm). In this analysis, the accelerations data of the subject were collected in term of accel_x, accel_y and accel_z where this values represent the rotation and orientation of the user’s hand movement in X-Y-Z axes.

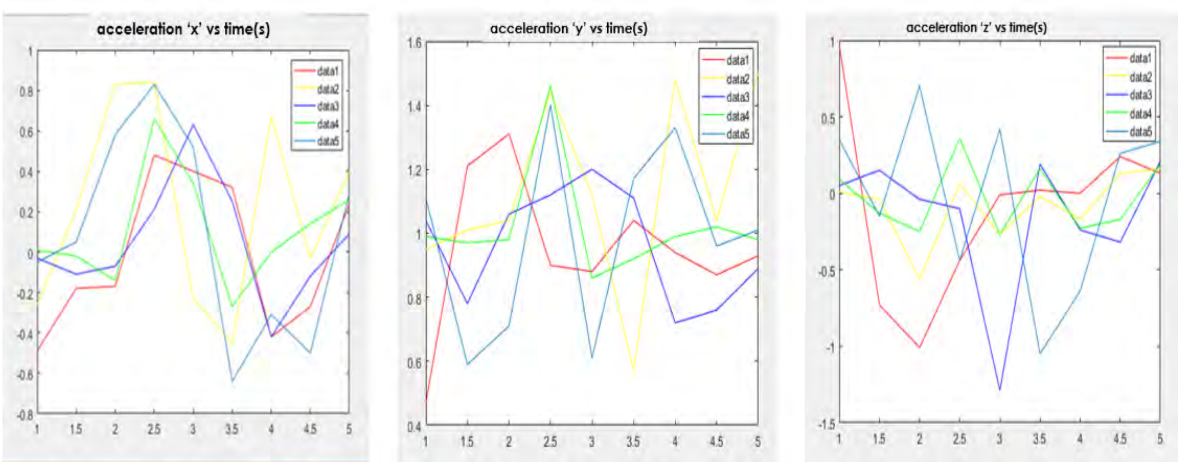

Figure 4.1(a): Data and graph of alphabet ‘a’

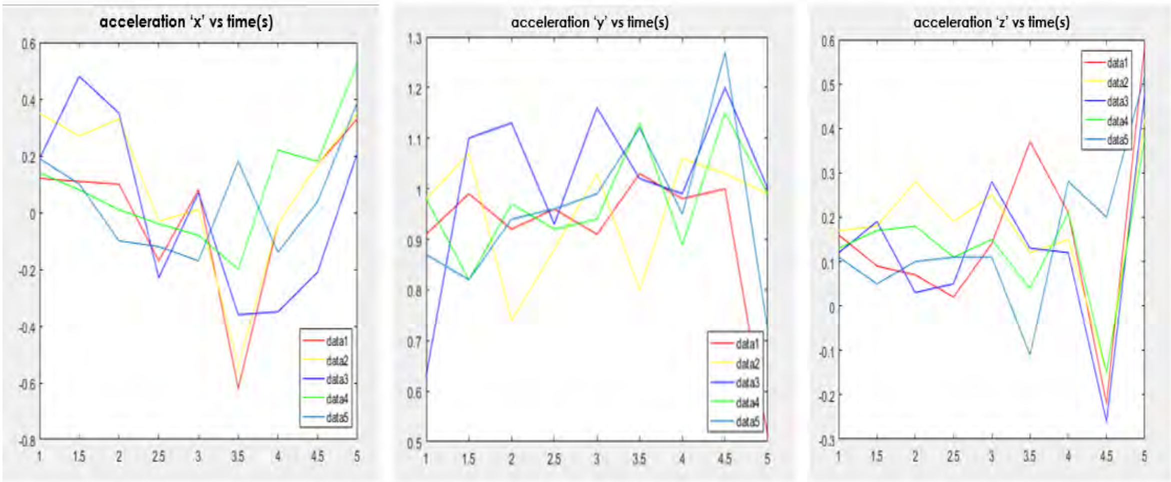

Figure 4.1(b): Data and graph of alphabet 'e'

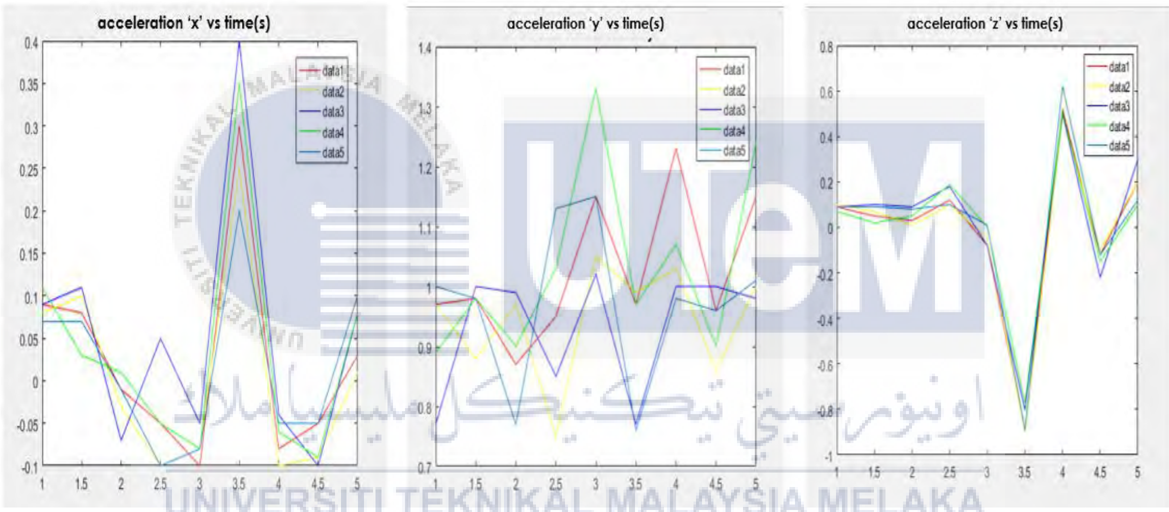

Figure 4.1(c): Data and graph of alphabet 'i'

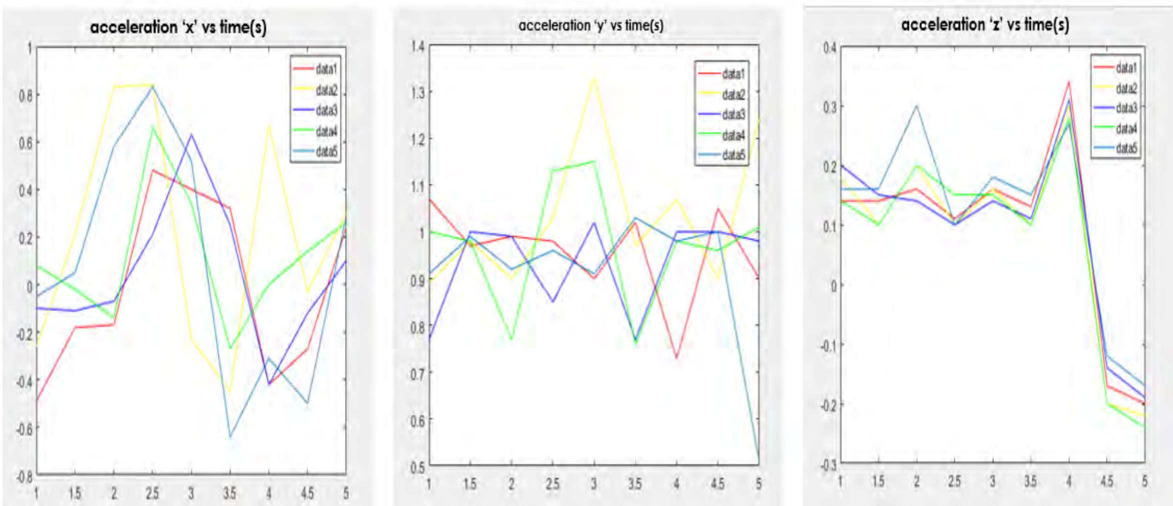

Figure 4.1(d): Data and graph of alphabet 'o'

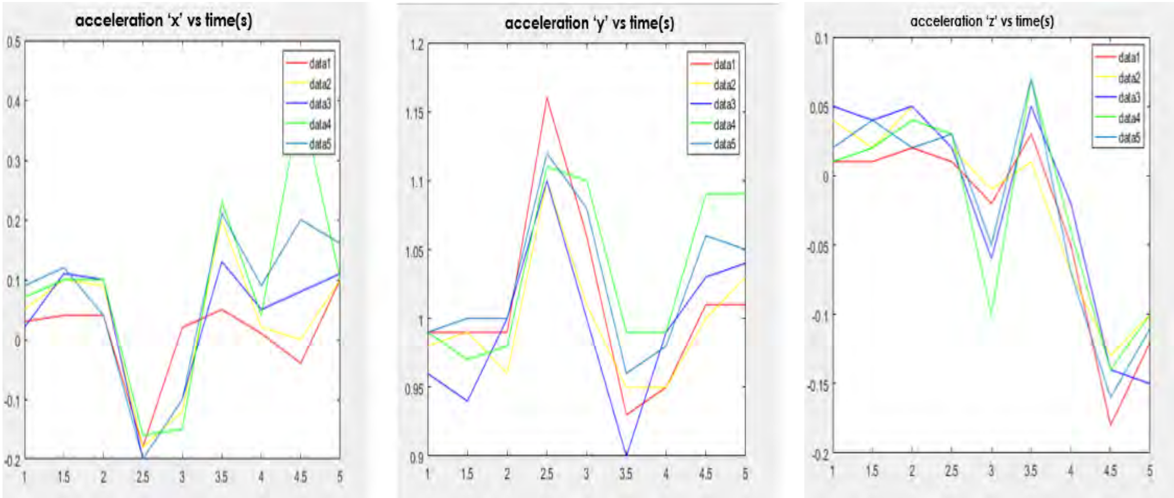

Figure 4.1(e): Data and graph of alphabet 'u'

The figures 4.1(a), 4.1(b), 4.1(c), 4.1(d) and 4.1(e) show the data and graphs of one selected candidate in developing the digital pen which can recognize the desired command by hand motion. As shown in the graphs (**acceleration against time(s)**), there were no huge changes in the values of accel_x,y,z data of each alphabet which remains in range of -1 to 1 per second except alphabet *'i'* as the subject of these five alphabet is the same user. Alphabet *'a'*, *'e'* and *'o'* only show a slightly difference in the data reading. This is because, the shape and writing movement of these alphabets are almost same. The graphs show by alphabet *'i'* were differ compared to other alphabets as this alphabet has different shape compared to others. The writing movement and hand orientation to write alphabet *'i'* was more simple than others. These data were considered when any movement acting on the X-Y-Z axes of the hand. Once the users start writing, the accelerometer sensor will measure the acceleration given by the users and come out with the x,y and z data. Each alphabet performed in different acceleration as each alphabet has its own shape. The acceleration readings and gesture orientation are different between the users as some users are left-handed and some are right-handed. The small changes that happened were caused by subject's writing posture which different for every alphabet and different from other subjects.

By applying the equation of mean, alphabet 'i' shows the highest accuracy which was 96.71% followed by alphabet 'u' that has accuracy of 90.71%. Alphabets 'a', 'e' and 'o' have almost same accuracy which were 82.81%, 83.72% and 85.13%. The accuracy depends on the acceleration and the hand gesture of the writing. Since 'i' has most accurate values of acceleration and the simplest hand gesture so it shows the highest accurate recognition rate compared to others.

4.1.2 Simplified Data Using Mean Equation

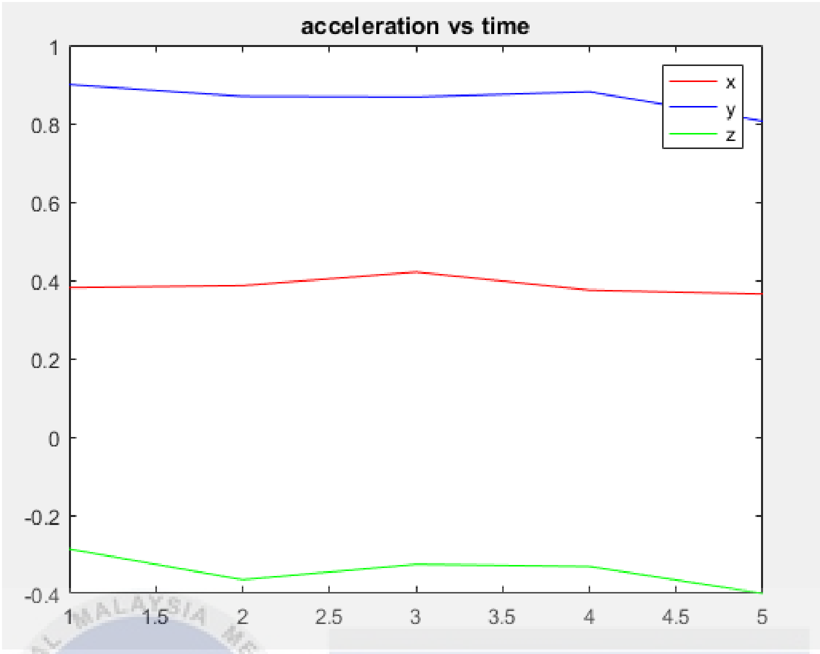

Figure 4.1(f): First Candidate's Handwriting Graph of Alphabet O

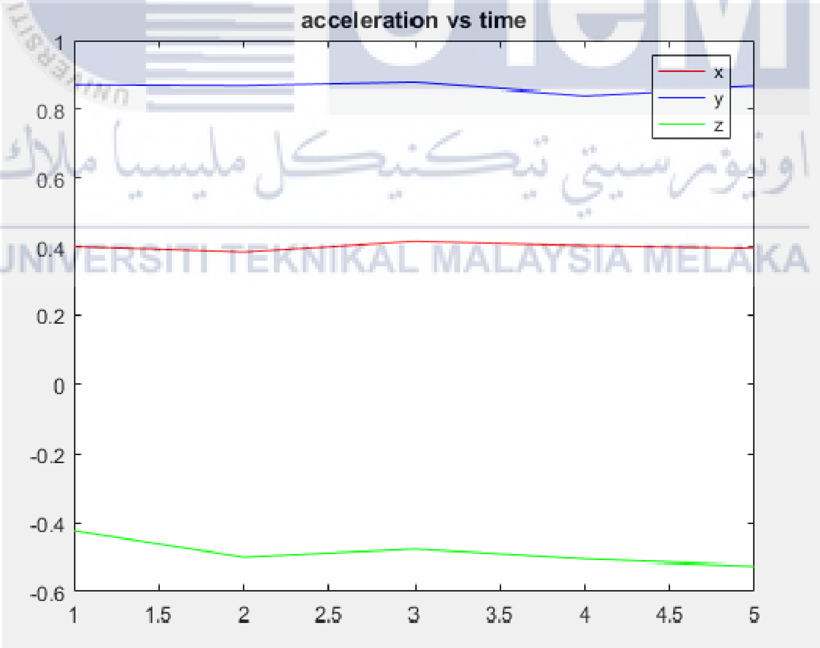

Figure 4.1(g): Second Candidate's Handwriting Graph of Alphabet O

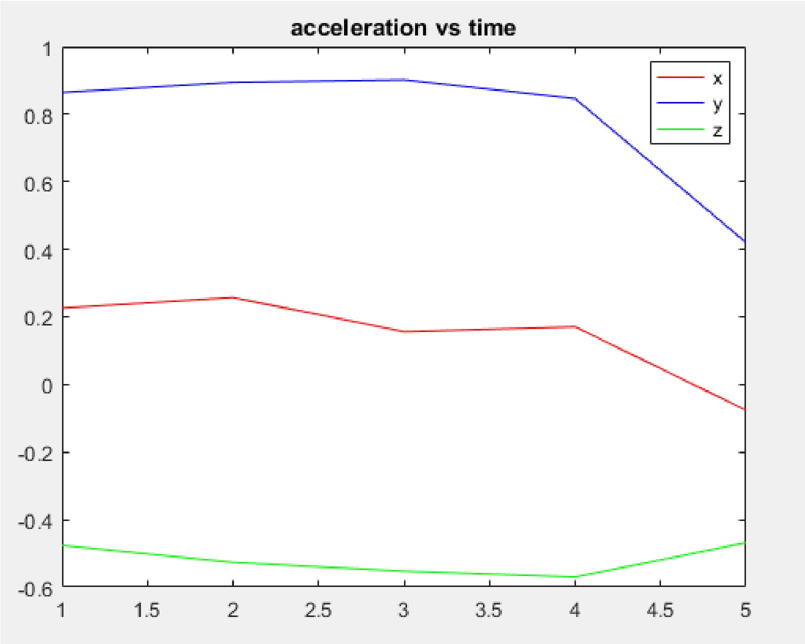

Figure 4.1(h): Third Candidate's Handwriting Graph of Alphabet O

Figures 4.1(f), 4.1(g) and 4.1(h) above shows the graphs of simplified data of alphabet 'o' from selected candidates (three students). Before plotting the graphs, all raw data was simplified using mean equation. Vowel 'o' was selected because the shape of this vowel encompasses all the writing dimension as it is nearly round shape. The plotting on these graphs were almost same for all the three axes which mean the hand gesture and handwriting acceleration of the candidates were nearly same. From the calculation, the mean average (x, y, z) data of first, second and third candidate were slightly difference (0.3854, 0.8646. -0.3414), (0.4000, 0.8631, -0.3870) and (0.4294, 0.8768, -0.4047) respectively.

4.2 Handwriting Classification

4.2.1 Handwriting Performance Using Neural Network

In this section, the performance of the handwriting recognition was validated in neural network. The overall data that will be use in this section were 500 in total where the raw acceleration data from the IMU sensor have been simplified using mean equation. For training the handwriting data were set up to 60% (300 data), 20% (100) of data were set for validation and another 20% (100) of the data were used for test in neural network simulation.

Table 4.2.1 shows the values of calculated performance metrics during training, validation and test in neural network by using the equations (3.4 - 3.7) stated in chapter 3. The values from confusion matrix have been calculated and classified into *true positive rate (tp) and false positive rate (fp).* Besides, from the calculation each class accuracy and precision can be determined.

During training in neural network, class 5 shows the highest accuracy of 77.6% while class 1 was less accurate with accuracy of 64.2%. The accuracy of class 2, class 3 and class 4 are 66.1%, 71.2% and 69.8%, respectively. The accuracy of all classes during training were slightly different, shows that the candidates have almost same hand gesture and way of writing. During validation of data in neural network, class 2 accuracy was almost perfect, 94.1% and the highest compared to others followed by class 5 which is 75% accurate. Class 4 and class 1 shows a slightly difference of accuracy, 65% and 64.3% followed by class 3 as the least accurate; accuracy of 59.3%. The accuracy of class 5 after testing in neural network was the highest, 70.6% followed by class 2 with accuracy of 69.2% while class 1 was least accurate compared to others with accuracy of 45.5%. The test on class 3 and class 4 achieve accuracy of 55.2% and 52.6%, respectively. Generally, most of the accuracy during testing were lower compared to training and validation. This may occur because of the overfitting model as the model maybe has learned particulars that help it perform better in the training data that are not applicable to the smaller data population and therefore the result in worse performance for test set. This case can be improved by improving the model (change parameter) or try a different machine learning algorithm.

Table 4.2: Calculated performance metrics from confusion.

Class		1	2	3	4	5
Training (%)	$tp\ rate$	20.6	17.7	22.5	17.7	21.5
	$fp\ rate$	8.61	8.1	6.7	11.5	8.6
	$precision$	70.5	68.5	77.0	60.7	71.4
	$accuracy$	64.2	66.1	71.2	69.8	77.6
Validation (%)	$tp\ rate$	26.0	23.2	23.2	18.8	8.7
	$fp\ rate$	7.2	11.6	4.3	11.6	10.1
	$precision$	78.3	66.7	84.2	61.9	46.2
	$accuracy$	64.3	94.1	59.3	65.0	75.0
Test (%)	$tp\ rate$	17.5	15.8	28.0	17.5	21.1
	$fp\ rate$	10.5	22.8	7.0	14.0	21.1
	$precision$	62.5	40.9	80.0	55.6	50.0
	$accuracy$	45.5	69.2	55.2	52.6	70.6

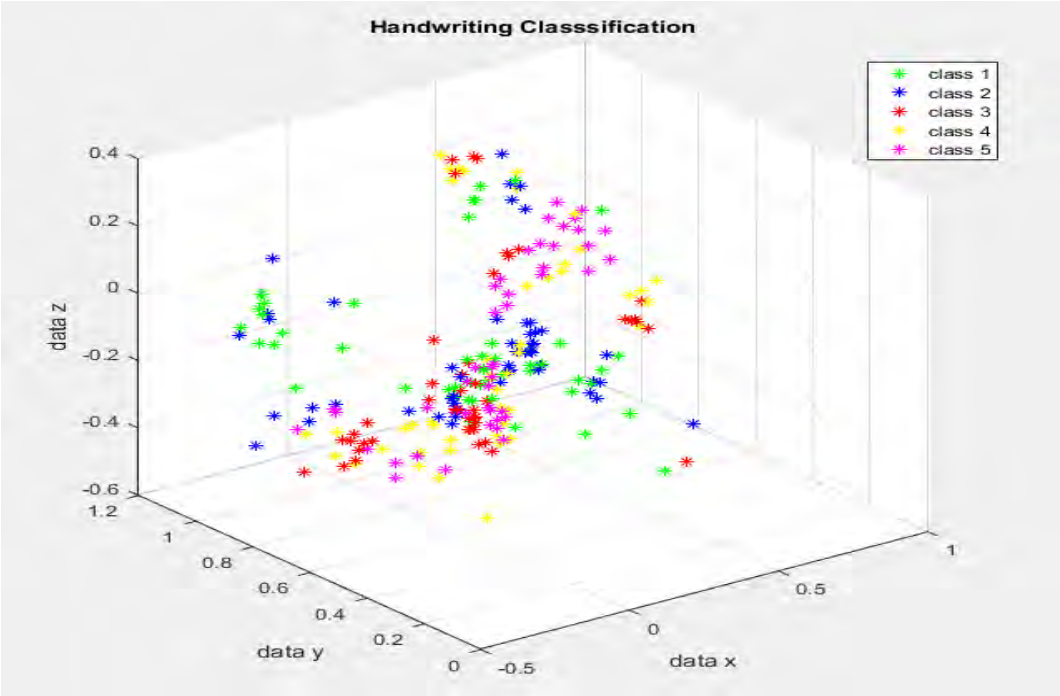

Figure 4.2(a): Handwriting Classification 3-D Plot.

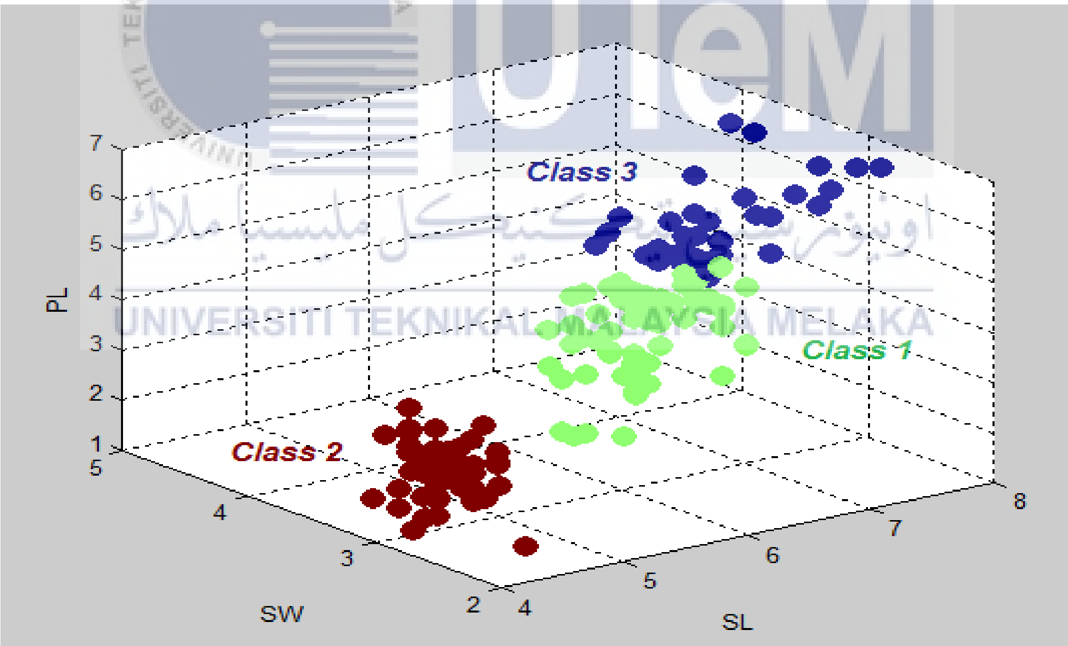

Figure 4.2(b): Classification On Handwriting [2].

As shown in the Figure 4.2(a), there are no huge changes in the values of accel_x,y,z data of each alphabet which remains in range of -0.6 to 1 for all axes. Each character's classes tend to cluster together and caused the recognition rate of correct classification and incorrect classification achieved after the neural network simulation were slightly different; 57% for correct classification and 43% for incorrect classification. From the plotting, all classes of the alphabet were overlapping to each other because all the alphabets were written for small size (5mm x 5mm). Although each alphabet performed in different acceleration as each alphabet has its own shape and the acceleration readings and gesture orientation were different between the users as some users are left-handed and some are right-handed, but the classes tend to overlap to each other because the size of the characters are small and the shape and writing movement of these alphabets are almost same. The small changes that happened were caused by subject's writing posture which different for every alphabet and different from other subjects. Compared to 3D plotting from previous research in Figure 4.2(b) [2], the classification boundary of the plot in Figure 4.2(a) can't be form correctly as the classes were overlapping to each other. All classes in Figure 4.2(b) [2] were plot perfectly. Only one or two data were overlapping to each other.

4.2.2 Development of Recognition Using GUI

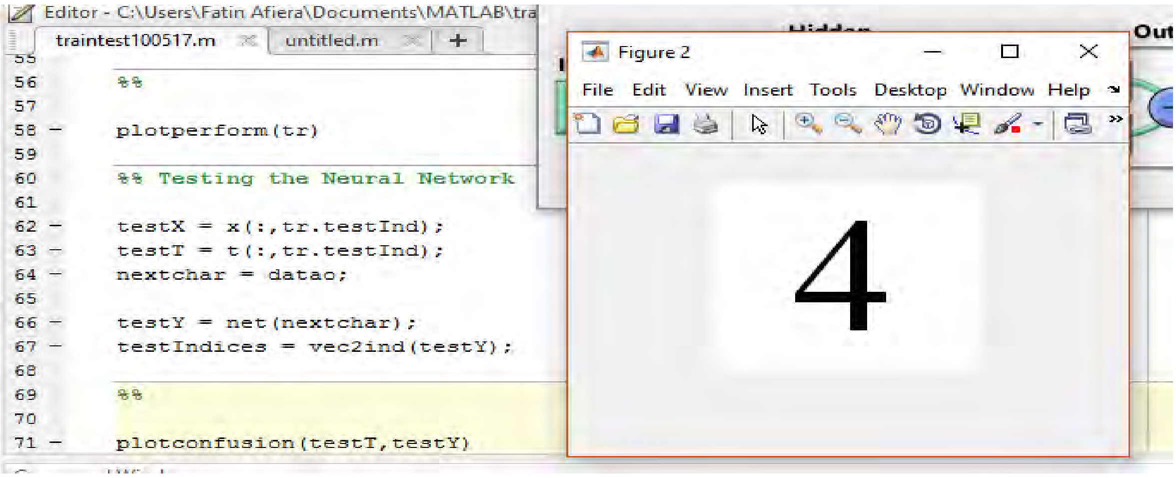

Figure 4.2(c): Digit 4 Recognize On GUI.

The Figure 4.2(c) shows the neural network simulation result for alphabet 'o' where the output was set up as digit 4 that represent the alphabet 'o'. To show simulated result in MATLAB, a graphical user interface was constructed which show the recognize output. Once handwriting data was collected from Arduino, the data then imported into MATLAB and the simulation start running.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

All objectives of this project were achieved successfully. First objective was to develop an experimental digital pen using IMU sensor which can recognize desired command by hand motion to control the device. The hardware construction of digital pen consists of Arduino Nano, IMU sensor, connecter wires as the transmitter and a USB as the receiver to transmit and receive the signal. All the setup has been done by implementing the hardware to the subjects and asked them to write the selected five alphabets to collect the data. The raw data collected and then imported into the MATLAB software to test the accuracy of IMU sensor. From the simulation, the overall accuracy of IMU sensor in recognizing the desired command was 87.82%.

Some features extraction and selection were carried out to extract the handwriting data in order to achieve the second objective of this project which is to extract important features from the sensor for the handwriting recognition. Feature extraction was used to simplified the raw data to the simplest value before importing into neural network for handwriting classification.

Neural network was implemented in this project to analyse the performance of the digital of small handwriting recognition; objective three. The input layer of neural network was fed up with three inputs which are data for x-axes, y-axes and z-axes for each alphabet. The number of neurons in the hidden layer are set up for 25 neurons. The hidden layers then link to output layer to produce the outputs. Five outputs have been set up that represent the class of the selected alphabets. Output 1, 2, 3, 4 and 5 represent the class of alphabets a, e, i, o and u respectively.

After implementing the neural network, the overall performance of the digital pen achieved was 57%. The 3-D plot shown in figure 4.2.1 (a) is related to the performance of recognition rate obtained from this project.

5.2 Recommendation

For the future work, the classification can be improved by improve the method to normalize and filter the raw data before doing the analysis. The performance of neural network can be increased by adding some more features other than the existing ones like standard deviation (STD) and root mean square (RMS). The development of the digital pen can be improved in term of generate command by hand motions to control electronic device without space limitation. The writing algorithms also can be developed for letters or words with multi-strokes which involve more challenging problems.

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APPENDICES

APPENDIX A: Arduino Program Code for Collecting Handwriting Data

```
#include <Wire.h>

long accelX, accelY, accelZ;
float gForceX, gForceY, gForceZ;

void setup() {
  Serial.begin(9600);
  Wire.begin();
  setupMPU();
}


void loop() {
  recordAccelRegisters();
  printData();
  delay(100);
}

void setupMPU() {
  Wire.beginTransmission(0b1101000); //This is the I2C address of the MPU (b1101000/b1101001 for AC0 low/high datasheet sec. 9.2)
  Wire.write(0x6B); //Accessing the register 6B - Power Management (Sec. 4.28)
  Wire.write(0b00000000); //Setting SLEEP register to 0. (Required; see Note on p. 9)
  Wire.endTransmission();
  Wire.beginTransmission(0b1101000); //I2C address of the MPU
  Wire.write(0x1B); //Accessing the register 1B - Gyroscope Configuration (Sec. 4.4)
  Wire.write(0x00000000); //Setting the gyro to full scale +/- 250deg./s
  Wire.endTransmission();
  Wire.beginTransmission(0b1101000); //I2C address of the MPU
```

```
  Wire.write(0x1C); //Accessing the register 1C - Acccelerometer Configuration (Sec. 4.5)
  Wire.write(0b00000000); //Setting the accel to +/- 2g
  Wire.endTransmission();
}

void recordAccelRegisters() {
  Wire.beginTransmission(0b1101000); //I2C address of the MPU
  Wire.write(0x3B); //Starting register for Accel Readings
  Wire.endTransmission();
  Wire.requestFrom(0b1101000, 6); //Request Accel Registers (3B - 40)
  while (Wire.available() < 6);
  accelX = Wire.read() << 8 | Wire.read(); //Store first two bytes into accelX
  accelY = Wire.read() << 8 | Wire.read(); //Store middle two bytes into accelY
  accelZ = Wire.read() << 8 | Wire.read(); //Store last two bytes into accelZ
  processAccelData();
}

void processAccelData() {
  gForceX = accelX / 16384.0;
  gForceY = accelY / 16384.0;
  gForceZ = accelZ / 16384.0;
}

void printData() {
  Serial.print(" Accel (g)");
  Serial.print(" X=");
  Serial.print(gForceX);
  Serial.print(" Y=");
  Serial.print(gForceY);
  Serial.print(" Z=");
  Serial.println(gForceZ);
}
```

APPENDIX B: Neural Network Code for Handwriting Classification

```
% Handwriting Classification
%% The Problem: Classify Handwriting Alphabets
% alphabets from different subjects:
% * Male
% * Female
% * Left-Handed
% * Right-Handed
%
%% Preparing the Data
% Data for classification problems are set up for a neural network by
% organizing the data into two matrices, the input matrix X and the target
% matrix T.
%
% Here such a dataset is loaded.

x = handwritinginputs;
class = handwritingtargets;
t = ind2vec(class);

% Note that both X and T have 500 columns. These represent 500 handwriting sample
% attributes (inputs) and associated class vectors (targets).

size(x)
size(t)
setdemorandstream(391418381)
%%
net = patternnet(25);
view(net)
% set early stopping parameters
net.divideParam.trainRatio = 0.60; % training set [%]
net.divideParam.valRatio   = 0.20; % validation set [%]
net.divideParam.testRatio  = 0.20; % test set [%]
```

```
% Now the network is ready to be trained. The samples are automatically
% divided into training, validation and test sets.

[net,tr] = train(net,x,t);
nntraintool

%%

plotperform(tr)

%% Testing the Neural Network

testX = x(:,tr.testInd);
testT = t(:,tr.testInd);
nextchar = dataa;

testY = net(nextchar);
testIndices = vec2ind(testY);
%%
plotconfusion(testT,testY)

%%
% Here are the overall percentages of correct and incorrect classification.

[c,cm] = confusion(testT,testY);

fprintf('Percentage Correct Classification   : %f%%\n', 100*(1-c));
fprintf('Percentage Incorrect Classification : %f%%\n', 100*c);

%%

plotroc(testT,test)
```