The Multimodal Interaction through the Design of Data Glove

By

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Abstract

In this thesis, we propose and present a multimodal interaction system that can provide a natural way for human-computer interaction. The core idea of this system is to help users to interact with the machine naturally by recognizing various gestures from the user from a wearable device. To achieve this goal, we have implemented a system including both hardware solution and gesture recognizing approaches. For the hardware solution, we designed and implemented a data glove based interaction device with multiple kinds of sensors to detect finger formations, touch commands and hand postures. We also modified and implemented two gesture recognizing approach based on support vector machine (SVM) as well as the lookup table. The detailed design and information is presented in this thesis. In the end, the system achieves supporting over 30 kinds of touch commands, 18 kinds of finger formation, and 10 kinds of hand postures as well as the combination of finger formation and hand posture with the recognition rate of 86.67% as well as the accurate touch command detection. We also evaluated the system from the subjective user experience.

Acknowledgements

Each ordinary people might all have dreamed about making this world a little different through their own effects. This was what I am thinking the most when I was doing my research, and it surely will be the heartfelt feeling of every men and women in academic field which is making some theories have been developed, some approaches can be applied and pushing forward for the human process by their own ideas experiments, proving and improving.

I would like to sincerely thank to my supervisor Prof. Abdulmotaleb El Saddik for his hard efforts to lead MCRLab as a world famous laboratory. I'm heartfelt appreciate his help on both academic guidance as well as the philosophy of life. I would also like to special and sincere thank Dr. Hussein Al Osman for his guidance, feedback and recommendation as my co-supervisor.

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Table of Contents

List of Tables

List of Figures

List of Abbreviations

HCI: Human-computer interaction

3D: Three dimensional

MCU: Microcontroller Unit

PC: Personal Computer

ASL: American Sign Language

UI: User Interface

GUI: Graphical User Interface

TUI: Tangible User Interface

ID: Identification

SVM: Support Vector Machine

HCI: Human Computer Interaction

ANN: Artificial Neural Network

HMM: Hidden Markov Model

OSI: Open Systems Interconnection

DIP Distal Interphalangeal

PIP: Proximal Interphalangeal

MCP: Metacarpophalangeal

I2C: Inter-Integrated Circuit

Chapter 1 Introduction

1.1 Background and Motivation

A “wearable device” refers to a portable device which can be worn directly on the body or can be integrated into a user’s clothing or accessories. It is not only a hardware device, but also a whole system which can achieve powerful functions with the support of software, the exchange of data, and the interaction with a cloud server. Existing wearable devices include those major classes: smart clothing, watch based, shoe based, and glass based [1].

In 2012, Google announced an important research project: Google Project Glass [2], which helps users expand reality by voice commanding a camera, video calling, navigation, and surfing the Internet. Despite the fact that it is powerful for its advanced diffraction display and numbers of applications, several arguments against aspects of Project Glass are still challenging these kinds of devices because of the high cost of the device, restriction in some public place by law for privacy purpose and so on. Watch based wearable devices are already very popular in the market; besides smart watches like Moto 360 [3], Samsung Gear [4] or Apple Watch [5] that possess their own operating systems, a large number of fitness trackers that come in the form of wristbands can also be classified in this category. Similar to wrist fitness trackers, shoe based wearable devices usually are used for fitness tracking and health monitoring. The discussion about wearable devices and the affiliated area: human-computer interaction (HCI) have become an extremely popular topic both in academic and daily life. The emergence of a large number of wearable devices [6] has significantly improved the overall experience of the operation of computers or other smart devices, since these devices have introduced multimodal interaction such as touch, voice, and motion detection etc.

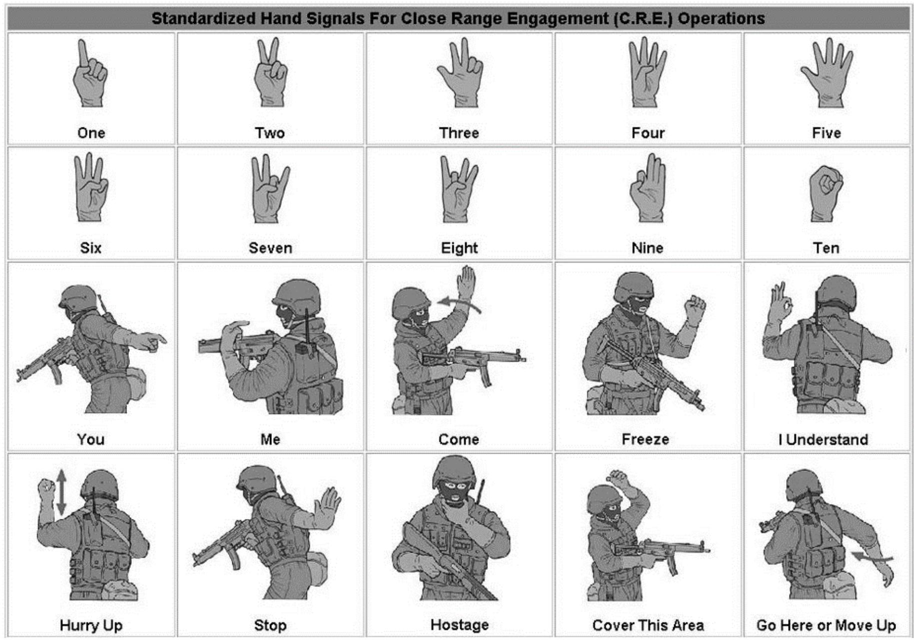


Fig. 1.1. Military Gestures including numeric information and battle commands [7]

"Human gesture" refers to a kind of human language for non-verbal communication including the position and shape of hands and fingers [8]. It is one of the oldest communication tools. As gesture communication evolved, gestures were given different sorts of specific meanings and became the most powerful means of expression of information and emotion [9]. They can substituted or appended to verbal communication in different scenarios

Human gestures consist of combinations of different positions and angles of the hands as well as the fingers that can construct a variety of language systems in different scenarios. Military hand signals are shown in Figure 1.1. They are used for communication of instructions or information silently and can represent things from numeric information to battle commands.

Hand gesture recognition relates to several aspects of research including signal processing, software engineering and sensor technology which significantly improves the human-computer interaction. Currently, much research has been done in this area and can be classified into two types: machine vision based and wearable device based.

The Machine Vision method, utilizing image processing by the computer to analyze gestures, can be divided into two approaches [10]. The appearance based approaches [10] use fingertip detection in order to construct the hand framework. Model based approaches introduce a statistical pattern [10] to build the hand frame. Conversely, sensor based methods typically use electronic, magnetic, ultrasonic, or optical sensors, to collect data of physical displacements or rotations and recognize gestures by processing the corresponding data. Among these approaches, the most popular devices for gesture detection or hand movement detection are glove-based systems. Although these methods already provide good quality for gesture recognition, there are still some defects and room for improvement and we will discuss them in the next section.

Gesture recognition based HCI refers to an approach of HCI for better user experience in some specific situations. At present, this method is being used in many fields. Applications such as virtual reality, somatosensory games and so on. It provides a natural way for interaction without traditional tools like keyboard, mouse or touch screen.

1.2 Existing Problems

According to Morgan Stanley, wearable technology is a rapid growth business with a potential of 1.6 trillion dollars market. Yet, over the past three decades, few of the research projects pertaining to gesture recognition were evolved into products. Even though there is a great need for such devices, still, there are some existing problems that can be described as follows:

- **Limitation of Camera:** The current machine vision approaches for detecting gestures are able to reach an acceptable numbers of supported gestures. [] Nonetheless, cameras or optical sensors are typically setup in a fixed location which directly affects their portability. On the other hand, high precision recognition demands a high quality image for analysis which can be affected by low light, mechanical vibration, noise, unhealthy training model and so on; it also requires a direct line of sight between the sensor and subject. Given these facts, we need to eliminate as many negative factors as possible to make the system more portable and less susceptible to these issues.
- **Limitation of Supported Gestures:** Most of the sensor based gesture recognition systems either recognize the flexion degree of fingers or hand movement. Nonetheless, human gestures consist of both finger and hand behaviors. This limits the existing systems to only particular applications. This is because that these systems usually use one kind of sensor. However, multiple kinds of sensors should be used for collection of the signal. A more desirable system should support as many gestures as possible and the supported type of gestures should be combined to match the original concept of hand

gestures, not carried out separately to adapt different requirement of different applications as possible. Therefore, we should build the system with multiple types of sensors to gather data with more degrees of freedom.

- **High Cost and Complex Setup:** Both approaches engage complex and expensive setups which will not be easily accepted by typical users. With the development of IC technology, building a low cost hand gesture recognition system becomes possible, and with a proper algorithm for processing data, we should be able to solve the complex setup issue.

1.3 Objective and Contribution

The expending need for the wearable device with a natural way of interaction drives the development of the multimodal interaction system. In this research work, we developed a multimodal interaction wearable system for improving the human-computer interaction experience by utilizing multiple kinds of sensors and building a low-cost, portable data glove which support numerous gestures and which provides a positive user experience.

The principle contributions of this research work can be summarized by the following points:

- **Gesture recognition method:** Design and development of a gesture recognition method that combines multiple techniques including lookup table and support vector machine (SVM), and offers better accuracy for distinguishing gestures in a wearable device based gesture recognition system. This approach contributes to the increasing demand for wearable devices used for the purpose of HCI.

The gesture recognition approaches that we have developed are as follows:

- A mathematical model for defining gestures including position and rotation of hand, flexion degree of fingers, as well as touch commands on the hand.
- The introduction of lookup table method and SVM for processing data from sensors and doing gesture recognition.

- **Multimodal interaction system:** Design and development of a wearable data glove system that consists of hardware and software design and implementation. The wearable data glove collects hand gestures including finger formation, hand posture and touch commands. We tried to settle the common problems of similar systems such as high cost, limitations of supported gestures, and optimized user experience.

For the Multimode interaction system, the main contributions are:

- Design of the multimodal data glove includes the setup of three kinds of sensors: resistance rheostat sensors, flex sensors and a motion sensor, the design of circuit of these sensors for signal acquisition.
- The design and implantation of software function includes the organization, transmission and process of data and the design of a new type of multimodal interaction interface allows user to interact with computer though different kind of gestures.

1.4 Thesis Organization

The remainder of the thesis is organized as follows:

Chapter 2 presents the background and related works. We also compare the previous research or products to our achievements in several aspects.

Chapter 3 proposes the idea of the multimodal data glove. It also extends to the detailed design of the hardware of the system.

Chapter 4 explains the implementation of the system by introducing the hand gesture recognition algorithm which cooperated with the hardware parts. The system result and performance from evaluation will also be provided.

Chapter 5 summarizes the entire work, draws conclusions, and provides the potential future work.

Chapter 2 Background and Related Work

Users and software developers have been constantly looking for the best way to interact with computers. The design of the input device plays a significant role in shaping the interaction experience. Wearable devices present a new and innovative method to interact with computers. Interaction with hand gestures is considered as one of the most natural methods. Hand gestures form a non-verbal communication language consisting of the position and shape of a hand and fingers. In order to utilize this method, many research contributions and commercial products have been proposed over the years and can be classified into two categories: machine vision based and wearable device based. The sensor based method for determining gestures uses an exact signal from different sensors and processes the signal for detection. Machine vision based approaches analyze images or videos to build a digital structure of the human body, and to determine the gesture. In this chapter, we will provide a brief overview of gestures, and introduce approaches to determine gestures for human-computer interaction.

2.1 Human gesture and sign language

A gesture refers to the combination of positions and shape of a hand and fingers and is a communication tool built by the speech center of our brain [8]. Gestures were given different meanings in social practices and possess a high level of expressiveness and they play the most important role in body language [11]. Sign language is a combination of gestures and sometimes facial expressions typically used for inter-human communication. It can express everything from simple numbers (see in figure 2.1) to complex sentences. It is often used in a variety of situations; for instance, deaf individuals use sign language as an alternative to spoken language, soldiers use sign language to transfer commands or information, and basketball referees communicate through sign language to express various decisions. Generally speaking, sign language can convert spoken language into an alternative visual form.

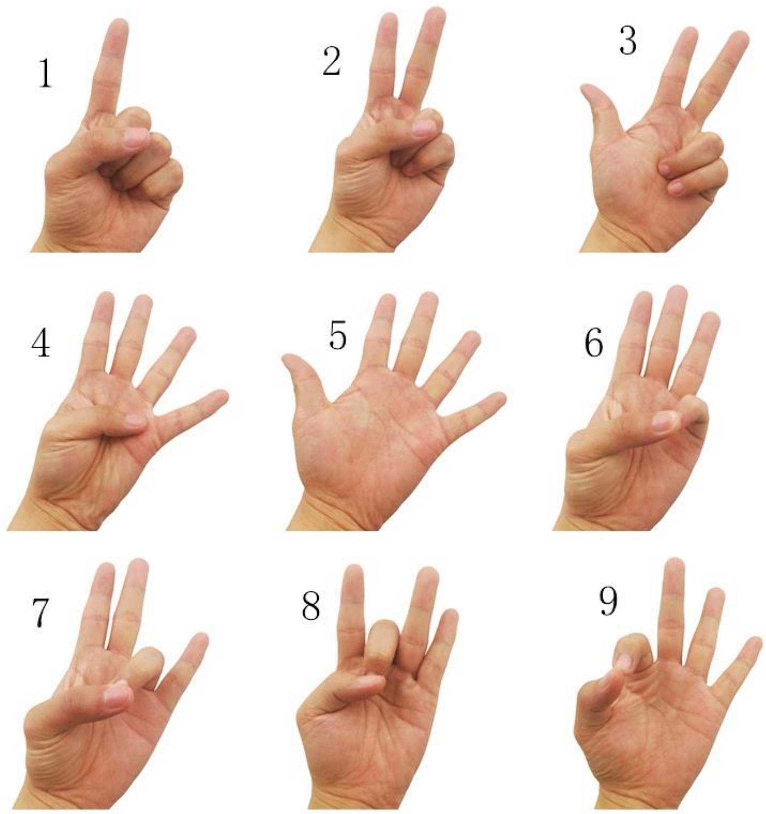


Fig. 2.1 Sign language hand positions for numbers [12]

In order to process the gesture data on computer, we divided the hand gesture into the following gestural components by detection methods:

Fingers formation: Each formation is characterized by the set of angles of all pairs of finger segments connected by a joint.

- **Hand posture**: Each posture is characterized by the set of angles of all pairs of arm segments (excluding the fingers) connected by a joint.
- **Touch commands**: Each command is triggered by the contact between the index, middle, ring or small finger belly or tip with the thumb pad, tip or hand palm

Compared to spoken language, gesture based communication methods or sign languages are considered as natural ways for communication, and have the following advantages:

- They can be used in some environmental circumstances requiring silence, such as Special Forces police operations since they do not need sound as the transmission medium.
- A single gesture can encode a wealth of information which can be per-established following a particular protocol, and which provides more efficiency than the spoken language.
- Gesture communication methods and sign languages can be coded to allow only certain people to understand the semantics of the communicated messages.

With these benefits, gesture communication methods and sign languages deliver a platform for inter-human interaction and, as technology advances, they are being expanded to improve human to computer interaction.

2.2 Gesture based HCI

Gesture based human-computer interaction refers to the use of hand gestures or sign language to interact with a computer. The core technique for gesture based HCI is the analysis or recognition of a gesture. Gesture communication methods or sign languages use the combination of the finger formation and hand posture. Two main approaches have been developed for acquiring and processing the various features of data required to detect gestures: wearable device based and machine vision based [13]. We will discuss these approaches in details.

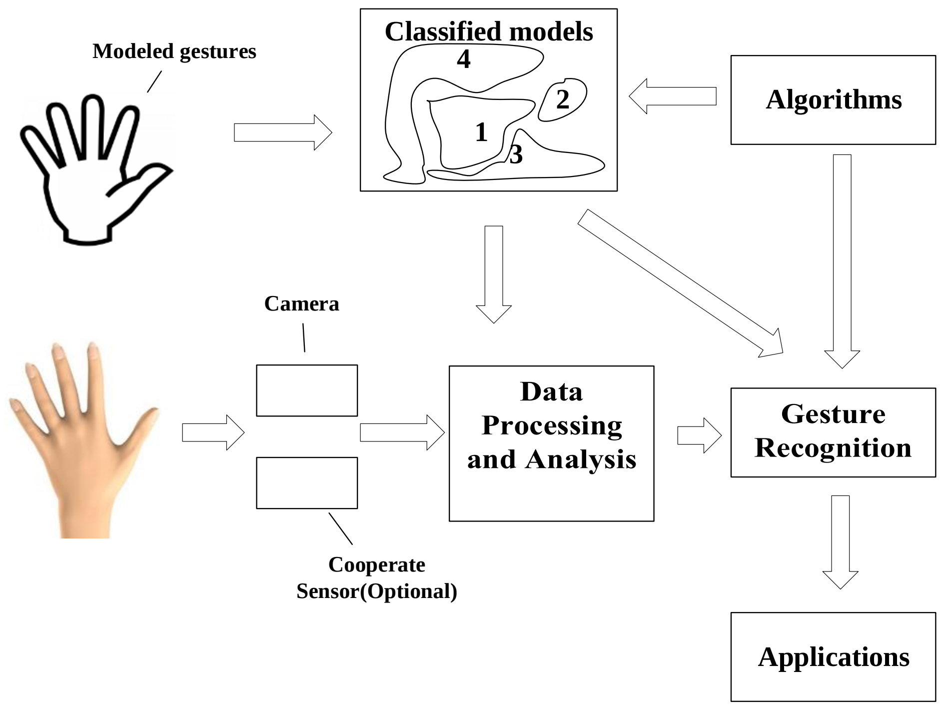


Fig. 2.2 Machine vision based gesture recognition process sequence [14]

The interaction based on gesture can be varied, and there are many applications on the market such as virtual environment applications [15][16], gaming simulators [17], 3D modelling [18], robot controls [19], communication tools for deaf people [20][21], mobile computer controls [22], medicine and rehabilitation [23][24] and so on.

2.2.1 Machine Vision based hand gesture HCI

Machine vision based gesture recognition methods are widely used in research works and commercial endeavors [10]. A typical procedure for Machine vision based hand gesture HCI is shown in figure 2.2. We will delve into the various stages of that procedure in following sections.

2.2.1.1 Hand modeling [14]

Before gesture recognition, hand modeling should be performed. After hand modeling, features are extracted from the video taken by the camera and compared to the model previously built. By extracting and analyzing the features from the video, we are able to establish a gesture model database for a natural user experience. Gesture models have already been defined in other research fields such as linguistics and anthropology. As we mentioned above, human gestures are constructed by the combination of finger formation and hand posture; however, gestures should be first divided by finger formation and hand angles and movement. The visual image is used to determine these spatial modeling factors. Currently, the following are two of the most popular approaches in modeling hand gestures:

- **Appearance-based methods:** An appearance-based method analyzes the hand gesture by matching predefined gestures. Both two dimensional image/video and 3D tracking has been applied to this method. The main concerns in the analysis of factors for this method are geometry and motion parameters and the position and angles of the fingertips from the image/video. The method extracts the outlines of hands and fingers and builds a matrix of the outline points to form an approximation of the outline using interpolation nodes. Several works use fingertip recognition for building the hand gesture model. The GREFIT system [25] is one of those which uses fingertip recognition, deals with numerous hand postures, and contributes the following approaches for building a fingertip model of the hand such as drawing a histogram for colored marking of the fingertips and using multiple samples or images for the prototype. The system accepts a size of 192×144 pixel gray scale image for processing. An improved approach is proposed by Nguyen et al. [26] and accepts a 640×480 pixel image to build the hand model. A Gaussian model was used for skin extraction. The skin color distribution density function follows:

$$\mathrm{p(c|skin)} = \sum_{i=1}^{k} \pi_i \mathrm{p}_i(c|skin)$$

where, π_i are the weight factors of a component and k is the total number of components. A system is able to distinguish 14 predefined gestures and is designed and implemented by Ng et al. [27] using $[320 \times 240]$ pixel video for two hands.

- **Model Based methods:** In this method, relative joints and associated length is used to represent the hand model which has been widely used in biomechanics. The human hand consists of 14 pieces of phalange which form fingers, 8 pieces of carpals belong to the wrist and 5 pieces of metacarpals are for building the palm. Each joint presents a different degree of freedom (DOF). Besides M in 2.3, most of the joints in the wrist have a very limited DOF. Since the movement of the finger is determined by three joints, it has a very high degree of freedom. Kuch et al. summarized these joints in the following table:

Table 2.1 Angle Range of different joints of human hand [28]

Finger static constraints	$0 \le \theta^{y}_{MP,s} \le 90°$
	$-15 \le \theta^{x}_{MP,s} \le 15°$
Finger dynamic constraints	$\theta^{y}_{PIP} = {}^{3}/_{2}\,\theta^{y}_{DIP}$
	$\theta^{y}_{MCP} = {}^{1}/_{2}\,\theta^{y}_{PIP}$
	$\theta^{y}_{MP} = {}^{\theta^{y}_{MP}}/_{90}\left(\theta^{x}_{MP,converge} - \theta^{x}_{MP,s}\right) + \theta^{x}_{MP,s}$
Thumb dynamic constraints	$\theta^{y}_{DIP} = \theta^{y}_{MP}$
	$\theta^{y}_{M} = {}^{1}/_{3}\,\theta^{y}_{MP}$
	$\theta^{y}_{M} = {}^{1}/_{2}\,\theta^{y}_{MP}$

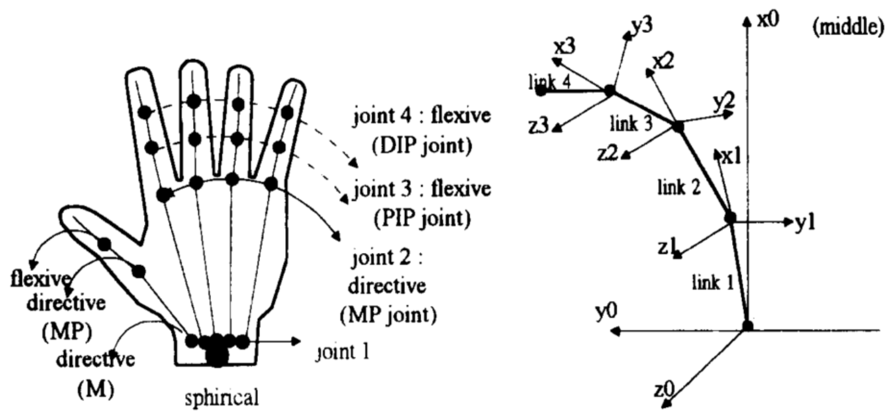


Fig. 2.3 (a) The hand model (b) Local coordinate of middle finger [29]

Using a camera and joint sensors to detect the illumination of the hand, Malassiotis et al. [30] developed a German sign language hand gesture recognition system. The system can build a three dimensional model of a hand. Lien et al. [29] defined a hand model with five degrees of freedom for the thumb and four degrees of freedom for other fingers, and developed local coordinates which take joints as an origin as seen in Figure 2.3. This approach provides the system with the ability to process the finger movement in a linkage combination. Finally, they proposed a fast model-fitting method for monitoring the movements of hand and fingers.

2.2.1.2 Hand gesture recognition

Hand gesture recognition in a computer vision based system analyzes models we described in section 2.2.1.1. Usually, there should be a training process involving the user before recognition. There exist several approaches aimed at recognizing different gestures by the computer vision method:

Hidden Markov model: HMM is an extension of the Markov Model which describes the Markov process with hidden parameters. It defines two stochastic processes: the first process describes the probability relationship between outputs and states while the second process describes the transitioning relationship between state and output, in which the transition between states is hidden. It has been used for gesture recognition. Generally, the 2D projection of a 3D hand model will be taken. Then a group of input features will be provided. The temporal part of the gesture will be mapped by the HMM classifier. The data will be applied for both training and testing the whole system. Because of the particularity of HMM's topology, the process of analyzing hand gestures could be extremely complicated. It needs a large quantity of training samples and recognition calculation results for a low speed of training and testing [31].

- **Finite-state Machine:** Gestures are built into a series in an ordered spatiotemporal model [32][33][34][35]. Different applications have different states. Therefore, gestures will be treated as continuous spatiotemporal models collected by sensors, and are represented as a set of points in sequence from two-dimensional space.

- **Soft Computing:** Soft computing can produce low costs and robust processing. It works in a similar way to the natural biochemical process in intelligent systems such as human perception, brain structure, and immune processes, which deal with daily work effectively. Genetic algorithms and artificial neural networks, along with other similar algorithms can undertake the task of gesture recognition. Defects of this method is obvious: the result is usually uncertain, imprecise and incomplete.

2.2.1.3 Applications

Computer vision based hand gesture HCI has a very wide range of applications. The most common one is to replace the traditional input of a computer, such as keyboard, mouse and joysticks [17]. Other applications, such as interpreters of sign language [20][21], are also being widely developed. Furthermore, the field of applications in a virtual environment is a huge branch which allows users to interact with virtual environment by the movement of hand and fingers.

The most significant factor of gesture recognition is the correct rate of recognition. The following table presents examples of research and their accuracy.

A lot of research works on machine vision based gesture HCI achieved very good results [36][37][38]. However, a disadvantage of this method is very evident: the requirement for a direct line of sight from camera to subject dictates that there will always be a camera in front of the subject and nothing should block the light propagation to the subject. Moreover, an inappropriate environment, such as a low light setting, can significantly impact the results.

Table 2.2 Computer Vision based human gesture HCI

Product or Research	Objective	Type of data collection	Recognition approach	Recognition Percentage
Staying Alive [39]	Tracking and gesture recognition	Hand and arm movement	HMM	N/A
[40]	Sign language	208 gestures	ANN	95%
[41]	Sign language	10 postures	ANN	90.45%
[42]	Sign language	40 words	HMM	90.7%
Real-Time Robotic Hand Control Using Hand Gestures [43]	Robotic hand control	10 postures	Principal Component Analysis	90%
Translation and Scale-Invariant Gesture Recognition in Complex Scenes [44]	Gesture recognition	10 gestures	Dynamic Space-Time Warping	96.3%,
Lee et al. research [45]	Gesture recognition	6 gestures	Pictorial information system	95%
Kinect[46]	Body tracking and gesture recognition	6 body postures, 8 hand gestures	Depth image analysis	N/A

2.2.2 Glove based human gesture HCI

Glove based gesture recognition for human computer interaction makes use of sensor gloves as the input. Unlike computer vision based approaches, this kind of method collects physical displacement and rotation of fingers and/or hands by sensors. Glove based gesture HCI has been developed for more than 30 years. Several typical examples, such as 5DT Data Glove Ultra [47], VMG 30 [48], CyberGlove [49] led advances in this approach. Dipietro et al. [50] summarized applications of glove based systems as follows：

- Applications in information and visualization which help to improve user experience when they are interacting with data
- An input device for design and manufacturing which typically was an input in a virtual environment
- Applications in robot programming which provide a natural and easy way for manipulating robots
- Applications which help an artist or game developer in tracing the animation of a human body, corroborated with other tracking techniques
- Applications which understand sign language by gesture recognition and can be used for both human to human interaction and human computer interaction.

Since, in this research, our focus is gesture recognition, we consider the following products or research in Table 2.3:

Table 2.3 Glove based human gesture HCI systems

Product or research	Objective	Type of data collection	Sensor(s)	Price
CyberGlove III [49]	Motion capture and graphic animations	Finger formation	Flex sensors	Very high
ShapeHand [51]	hand motion capture	Finger formation	Flexible ribbon sensors	Very high
5DT Data Glove 5 Ultra [47]	Motion capture and animation professionals	Finger formation Hand posture	Flex sensors Motion sensors	~ $900
DG5 Glove 3.0 [52]	Motion detection	Finger formation, hand posture	Flex sensors, motion sensor	~ $600
Peregrine [17]	Gaming device to replace keyboard	Touch commands	Resistor sensors	~ $150
MYO [53]	Computer and mobile device control	5 finger formations, wrist rotation	EMG sensor, motion sensor	$199

The peregrine Glove provides over 30 kinds of touch command but the lack of detection of finger formation and hand posture limits its application. MYO is a good product to interact with smart appliance and simple computer control since they just support 5 gestures. The peregrine glove and MYO are all in an acceptable price.

Based on the CyberGlove system, Gao et al. [54] achieved recognition of over five thousand words of Chinese sign language with about 90% average accuracy. Takashi et al. [55] developed a system for understanding Japanese alphabets (51 in total) with Data Glove. These related work on CyberGlove system proves that it has a very solid performance even without detecting other components of hand gestures. The way of

CyberGlove system to measure the hand posture is either use an outer skeleton or machine vision method which significantly limits the mobile use of this system.

Fig. 2.4 CyberGlove System [49]

5DT Data Glove 5 Ultra and DG5 Glove 3.0 all provide finger movement and hand orientation detection which could support a large number of gestures but none of them provides an approachable price since if we want to recognize gestures as many as possible, multiple kinds of sensors will be applied and that will increase the price of system exponentially. More importantly, no product or research combines all three components of hand gesture we talked before: finger formation, hand posture and touch command which will provides more supported gestures then other existing ones. Given these studies, we can conclude that the more gestures these systems are able to recognize, the higher the cost will be for the system.

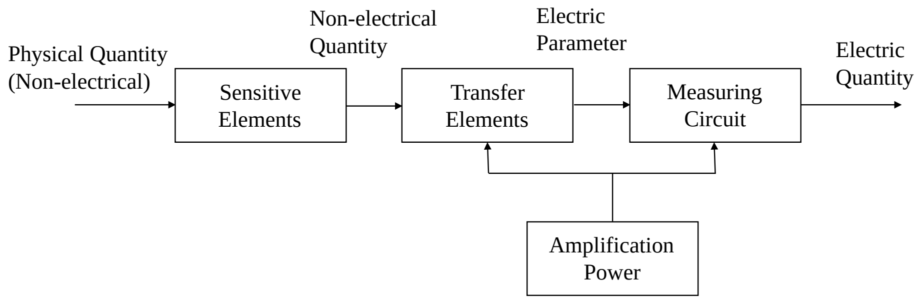


Fig 2.5 the working process of a sensor

Fig. 2.6 Flex sensor

In this research, we tried to challenge and solve those crucial disadvantages of both HCI method and wearable device method. Our proposed system will tried to support the same number of gestures as the previous ones without all-time monitoring camera on the side in an affordable cost.

2.3 Sensor

Sensors or transducers are components that can convert a physical quantity into electrical signals, which can then be detected by observers or instruments. Generally speaking, the working process of a sensor can be described as Figure 2.4.

In our research, we used multiple kinds of sensors such as a flex sensor, a resistance sensor and a motion sensor on the glove. They will be introduced in the following sections.

- **Flex sensor:** A flex sensor (seen in Figure 2.6) is able to increase its self-resistance when the metal pads on the sensor are flexed. It is able to detect the angle of displacement as a form of the changing voltage in a circuit.
- **Resistance rheostat sensor:** A resistance rheostat sensor is able to display position information. It presents different resistance when actuator triggers different position (Seen in Figure 2.7). The sensor itself can be seen as a changing registers and a changing voltage divider connected in series when the actuator in a closed circuit is pointing on a certain position on the sensor. As a consequence, the voltage of the trigger point will be changed at the same time. We usually monitor those voltage changes to determine the trigger position.

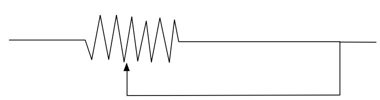


Fig. 2.7 Rheostat sensor

- **Motion Sensor: A** motion sensor can refer to various components: accelerometer, gyroscope, and/or digital compass. An accelerometer measures linear acceleration. Usually a digital accelerometer can detect three dimensions of the inertial force. A sensitive mass, a support part, a potentiometer, a spring, and dampers together construct a digital accelerometer. The coordinate space of a three dimensional accelerometer is vector space including x, y and z axis. We can determine linear movement by measuring different components from the x, y and z axes. Gyroscope is a device for sensing and maintaining directions. As opposed to the traditional gyroscope which uses the principle of the law of conservation of angular momentum, the micro electro mechanical gyroscope provides a low cost alternative. It makes use of Coriolis force – the tangential force of rotation object with radial movement. Although this kind of gyroscope is not precise, it can be calibrated with other sensors like digital compass, and that is why some manufactures sometimes assemble them together to achieve a higher accuracy.

2.4 Serial port

Serial port communication is a crucial part of acquiring data from the device to the processing unit in the glove based gesture recognition HCI system. The serial port is a common communication channel between a computer and its external devices. Serial communication occurs on the data level of OSI layers. On this layer, data is transformed by frames.

2.5 Support Vector Machine (SVM)

In our research, we applied SVM for processing data from gyroscope and recognizing different hand posture in different gestures since the system determine the hand posture by six dimensions of data: 3-axis data of gyroscope and 3-axis data of accelerometer and support vector machine is ideal for rapid and accurate identification on this kind of data set. The following sections will briefly introduce this algorithm.

SVM is a two-class classifier model. The basic definition of the model is a linear classifier for maximize the margin between different classes. The training strategy of SVM is to maximize the margin between classes and convert it into convex quadratic programming. [56]

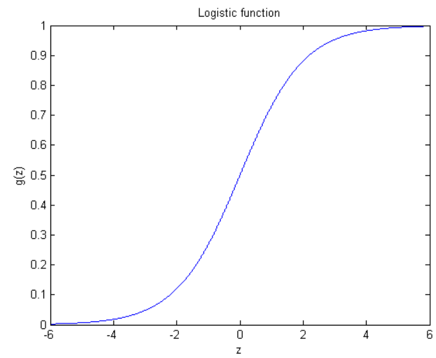


Fig. 2.8 Logistic function

2.5.1 Logistic regression

The goal of logistic regression is to build a model for classifying y=-1 and y=1 class. This model considers the linear combination of features as an independent variable. Since the range of the independent variable could be from negative infinite to positive infinite, we use a logistic function to map the variable from 0 to 1. And the value after mapping will be considered as the probability classifying feature to class 1.

Assume:

$$h_\theta = g(\theta^T x) = 1/(1 + e^{-\theta T}) \qquad (2-1)$$

where, x is an n-dimensional eigenvector and g is the logistic function.

It can also be written as:

$$g(z) = 1/(1 + e^{-z}) \qquad (2-2)$$

From Figure 2.8, we can see that the function maps an infinite range to a range from zero to one.

Therefore *g(z)* is the probability that the input x, with such features, belongs to the class of y = 1:

$$P(y = 1 \mid x; \theta) = h_\theta(x) \qquad (2-3)$$

$$P(y = 0 \mid x; \theta) = 1 - h_\theta(x) \qquad (2-4)$$

To determine the class, we check if $h_\theta(x)$ is over 0.5, then it belongs to the class of y=1, otherwise it belongs to the class of y = 0.

The next step is to transform the logistic regression. The labels are changed from $y = 0$ and $y = 1$ to $y = -1$ and $y = 1$. Since $x_0 = 1$, θ_0 is replaced with b from $\theta^T x = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n$. The function was transformed to $w^T + b$. In the end the value of $h_{w,b}(x) = g(w^T + b)$ is mapped to $y = -1\ and\ y = 1$ and have:

$$f(z) = \begin{cases} -1, & z < 0 \\ 1, & z \geq 0 \end{cases} \qquad (2-5)$$

2.5.2 Linear classifier

x and y is used to represent data and class. The learning goal for the linear classifier is to find a hyper plane in the n-dimension data space. The formula of hyper plane can be written as:

$$w^T x + b = 0 \qquad (2-6)$$

Now we have a two-dimensional plane with two classes of data. They can be divided into two classes by a line, which can be considered as a hyper plane:

$$f(x) = w^T x + b \qquad (2-7)$$

Where x is the point on the hyper plane when $f(x) = 0$. When $f(x) > 0$ it belongs to the class of $y = 1$ and when $f(x) < 0$ it belongs to the class of $y = -1$. (Seen in Figure 2.9)

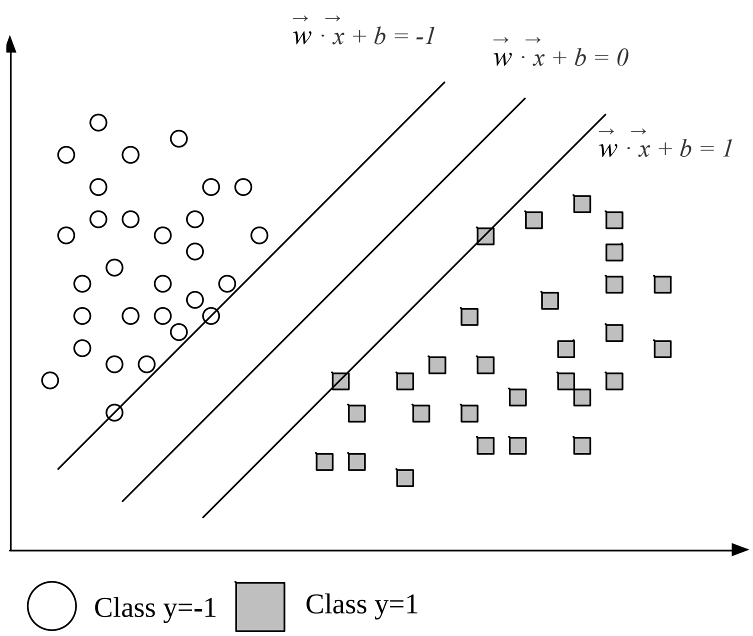


Fig. 2.9 Two class classification

2.5.3 Maximum margin

When the hyper plane $w^T x + b$ is certain, $|w^T x + b|$ can display the distance between x and the hyper plane. By observing the positive and negative of $w^T x + b$, the class label of y can determine if the classification is correct. Therefore, we can use the positive or negative sign of $y(w^T x + b)$ to determine if the classification is correct. Here we define a functional margin as:

$$\hat{\gamma} = y(w^T x + b) = yf(x) \qquad (2-8)$$

The problem of this definition is that when *w* or *b* change, the margin will change at the same time. So we need to add constraint conditions for the normal vector *w*.

We set a point *x* in the space and its vertical projection x_0 is on the hyper plane (*w*, *b*) (Seen in Figure 2.10). w is a vector which is perpendicular to the hyper plane. γ is the distance from sample x to the hyper plane. As a result:

$$x = x_0 + \gamma \frac{w}{||w||} \qquad (2-9)$$

Since x_0 is a point on the hyper plane, we have $f(x_0) = 0$. Take those into the hyper plane function:

$$\gamma = \frac{w^T x + b}{||w||} = \frac{f(x)}{||w||} \qquad (2-10)$$

In order to get the absolute value of γ we have to multiply γ with corresponding class *y* and have:

$$\tilde{\gamma} = y\gamma = \frac{\hat{\gamma}}{||w||} \qquad (2-11)$$

which is the geometric margin - the actual distance between x and the hyper plane.

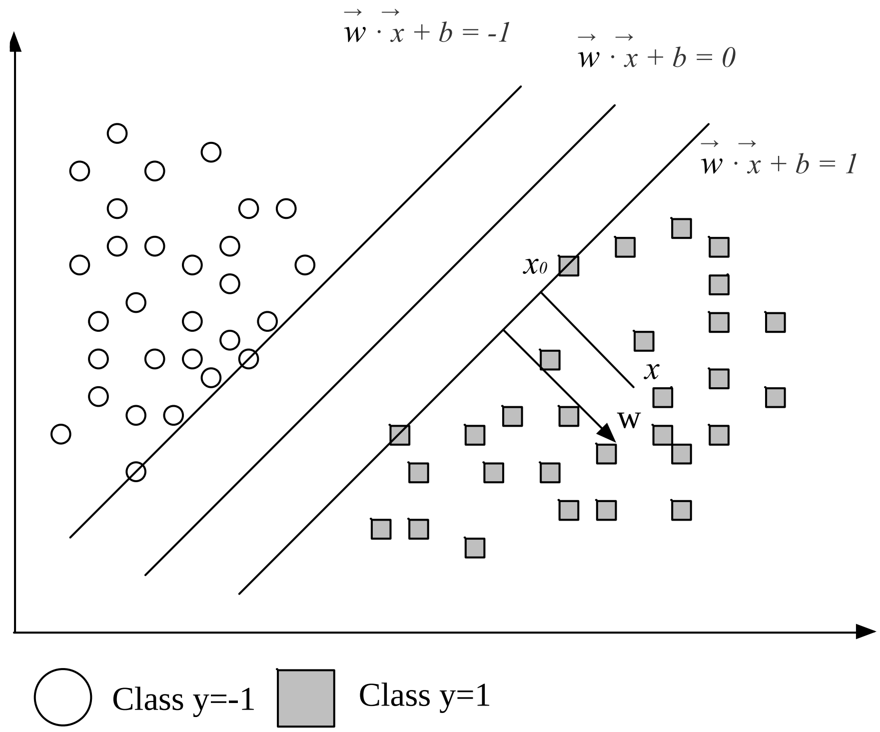


Fig. 2.10 An example of SVM

When we are classifying data, the larger the gap between the hyper plane and a set of data, the larger is the confidence. In order to get as high a confidence as we can, the selected hyper plane should be able to maximize the gap. Therefore, the objective function of the maximum margin classifier would be:

$$max\tilde{\gamma} \qquad (2-12)$$

subject to

$$y_i(w^T x_i + b) = \hat{\gamma}_i \geq \hat{\gamma}\ (i = 1,2,\dots,n) \qquad (2-13)$$

let $\hat{\gamma} = 1$, we have $\tilde{\gamma} = \frac{1}{||w||}$, s.t. $y_i(w^T x + b) \geq 1\ (i = 1,2,\dots,n)$ and the former formula can be transformed into:

$$max\frac{1}{||w||} \qquad (2-14)$$

subject to

$$y_i(w^T x + b) \geq 1 \ (i = 1,2, \dots, n) \qquad (2-15)$$

Referring to Figure 2.11, the bold line in the middle is the optimal hyper plane. The distance between the optimal hyper plane and the other two planes is equal. Those points on the sidelines are support vectors. This only considers the linearly separable situation, which is sufficient for our research. As for the other case, it will not be discussed in this paper.

Sometimes, there will be some noise in the gap between classes. We apply a soft margin to choose the hyper plane to avoid most of these noise data. The slack variable ξ_i determines the misclassification degree for the training sets. We change the objective function into another form: $min\ \frac{1}{2}||w||^2$. Considering the slack variable, we have:

$$\min(\frac{1}{2}||w||^2 + C\sum_{i=1}^{n}\xi_i) \qquad (2-16)$$

subject to

$$y_i(w^T x + b) \geq 1 - \xi_i \ (i = 1,2, \dots, n) \ and \ \xi_i \geq 0 \qquad (2-17)$$

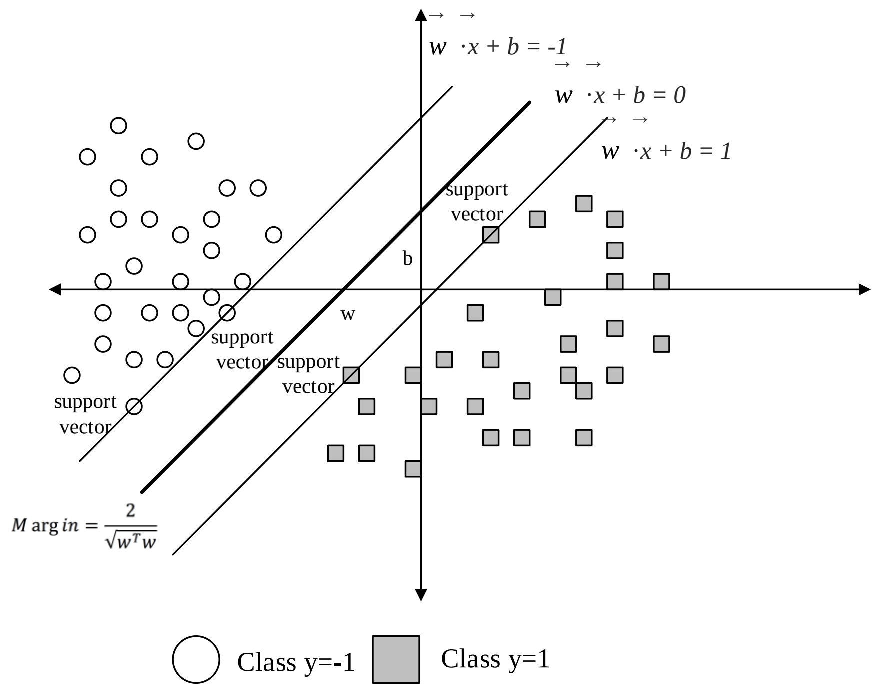


Fig. 2.11 Optimal hyper plane

2.6 Summary

In this chapter we briefly introduced the background knowledge and related work of this research. We presented the definition of human gesture and sign language, and expended the concept of hand gesture into three kind of gestural components: finger formation, hand posture and touch command. we discussed the gesture based HCI including machine vision based hand gesture HCI and wearable device based human gesture HCI and we proposed that the data glove we are going to develop should support all three gestural components we mentioned above. We briefly introduced the sensors used in our system as well as the communication method. Finally, we discussed the techniques that we will integrate into our gesture detection algorithm: linear support vector machine and lookup table.

Chapter 3 Proposed Multimodal Data Glove System

3.1 System Objective

As we mentioned in the existing problem of gesture-based human computer interaction, there are several drawbacks to the current approaches [9][57][50]. Therefore, the system we propose here should solve these problems in order to improve the human computer interaction. Specifically, we propose the following:

- **The system should be able to recognize more gestures:** From the related works, we know that computer vision-based gesture recognition supports a fair number of gestures For example, the Peregrine Glove support at least 30 kind of touch commands [17]. However, as we concluded in section 2.2.2, glove-based approaches tend to limit the supported gestures when it comes to a low cost solutions. Also, the type of supported gestures is limited. The glove based system we propose, should support as many gestures as possible. There is no research simultaneously support fingers formation, hand posture and touch commands.

- **Low cost and ease of use:** Most glove-based systems with multiple-type inputs require a large hardware expense, which limits the promotion of this type of solution. The system we propose should control the cost of hardware to be as low as possible. Meanwhile, the system we propose should be able to use in multiple purposes for a majority of users and the supported gestures in the system provided should be either common gestures or easy to remember.

3.2 System Overview

The data glove system we propose here is a glove-based system that allows a user to interact with a computing device. It supports all of the gestural components we described in section 2.1 including:

- Finger formation
- Hand posture
- Touch command

Some or all of the above mentioned gestural components can be combined to generate distinct gestures. Thus, the system we propose will offer a large quantity of gestures.

In order to detect hand gestures, a glove-based sensor system is proposed. We utilize a group of sensors to detect various gestural components. We use positional rheostat sensors to detect the contact between fingers and thumb or palm, flex sensors to determine the fingers' formation, and a motion sensor to monitor the hand posture. We also built an embedded system comprised of electric circuits and a microcontroller to collect the sensor analog signals, convert them to digital and relay them to a computing device. In order to recognize gestural information, we proposed a new hand gesture model which simplifies the former model [17] [47] [48] [49] for lower cost on sensors and fast response on recognition; the model will be introduced in section 3.4.2. We applied two proven methods: lookup table and linear SVM to develop three algorithms for recognition of different gestural components: lookup table based touch command and finger formation recognition algorithm and linear SVM based hand posture recognition algorithm. They will be discussed in section 3.4.3. We achieved a replacement solution for a keyboard and mouse by using the gesture recognition of the proposed system to manipulate characters in video games. We also improved the user experience in controlling a map application. Potential applications such as battle command transmission platform has also been proposed. The applications will be discussed in chapter 4.

The various system modules are shown in Figure 3.1. In our proposed system, gestural information is collected by the signal acquisition layer, made up of the system's sensors, as well their necessary circuitry. A microcontroller-based system will convert the analog signal into digital form so that the computer is able to process this data; it also acts as a data communication platform to connect the sensor with the upper computers or a host computer: ones can send and receive operation commands, usually is a PC. Signal processing follows the collection of data. We use three algorithms for three kinds of gestural components recognition in our system. The algorithms are based on lookup tables and linear SVM. We use the lookup tables for the detection of finger formation and touch commands, while the linear SVM is used for the detection of hand postures. After processing the data, the system generates a gesture ID and sends different commands to applications. Two types of systems have been proposed for different situations: the Type 1 system suggests that for simple gestures or postures, the microcontroller will be sufficient for determination, while Type 2 processes data in the upper computer due to its higher computing power for training models and classifies the input data into different gestures.

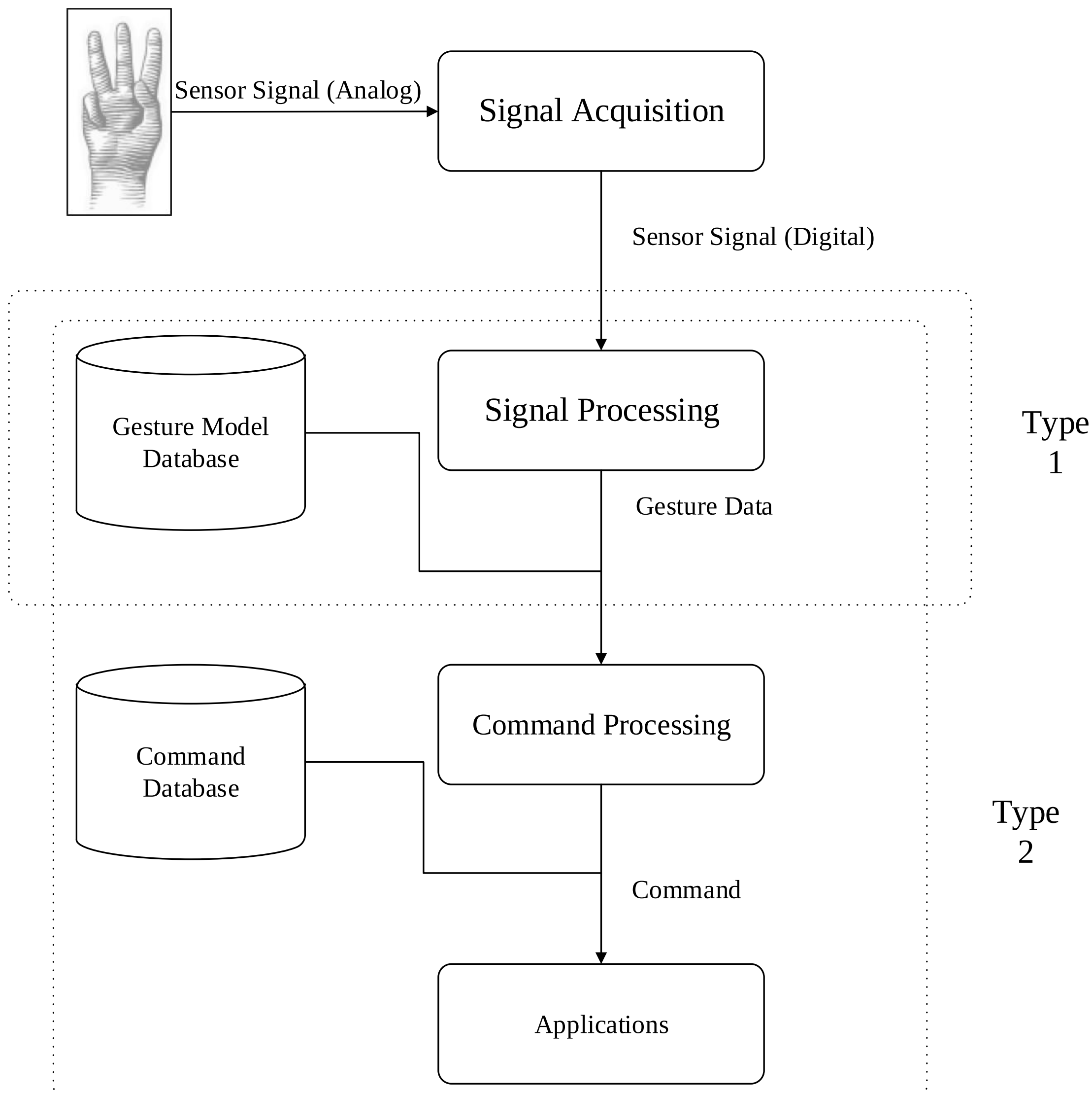


Fig. 3.1 System Structure

3.3 Signal Acquisition

The signal acquisition component of the proposed data glove is in charge of detecting and measuring the movement and rotation of the hand and fingers as well as the touch commands stimulated by the fingers. We employed three kinds of sensors to collect the necessary information for gesture detection:

- A Resistance rheostat sensor
- A flex sensor
- A multiple dimensional motion sensor

Corresponding circuits for each kind of sensor were also designed, built, and connected to a microcontroller system.

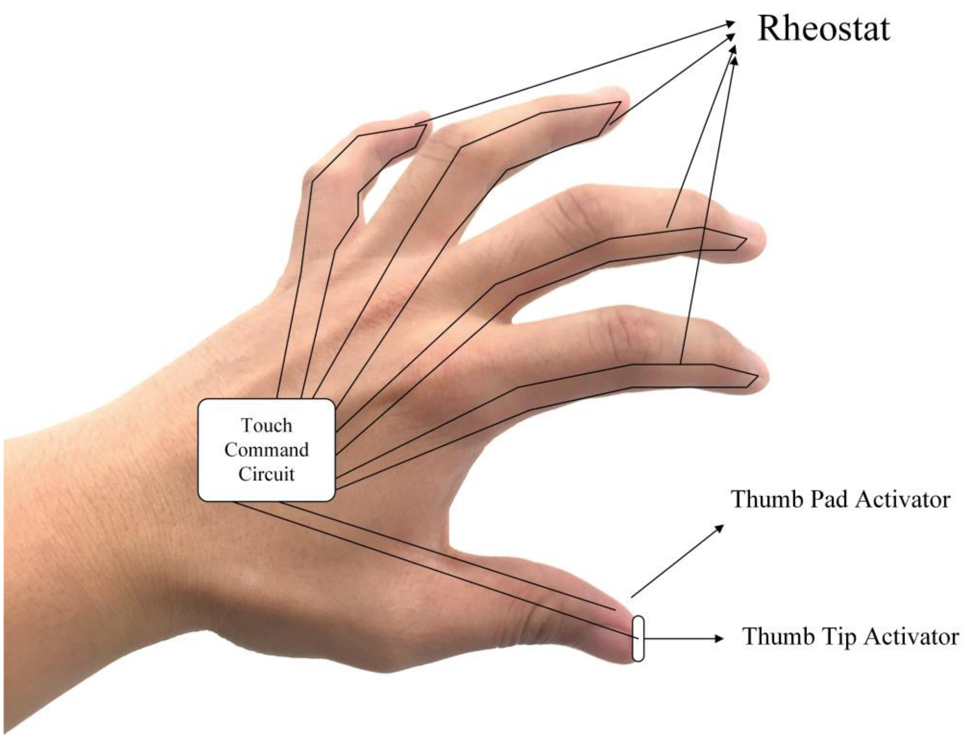


Fig 3.2 Touch sensor on the hand

3.3.1 Resistance Rheostat

The rheostat sensor we used is made of stainless steel with a high electric resistance. The self-resistance is changed by the different activing position. After doing background research, we discovered that a product called the Peregrine Glove with similar functions already existed [17]. In our research, we used their product as our base glove. We redesigned and built the detection circuit and only used their embedded sensors on the glove. The position of sensors is shown in Figure 3.2: rheostat sensors are placed on one side of little finer, ring finger, middle finger and index finger. Three activator are placed on thumb pad, tip and palm. User need to use one of these activator to touch a certain position on the sensor to issue a command.

Figure 3.3 shows the circuit for touch command detection. R1, R2, R3 and R4 are the rheostat sensors implemented on the little finger, ring finger middle finger and index finger of the user’s hand, respectively. These sensors are connected in parallel. We can also notice that R5, R6, R7, R8 are fixed resistors that have been connected in series with each rheostat sensor on each finger. In order to build step values of on different fingers, we set those fixed resistors to have different resistances. The switch in the figure is to represent the case when an activator touches the sensor, when it will build a new closed loop. Switch Sc is closed depending on which finger was touched. The output of this circuit is the measurement of voltage at the analog output point.

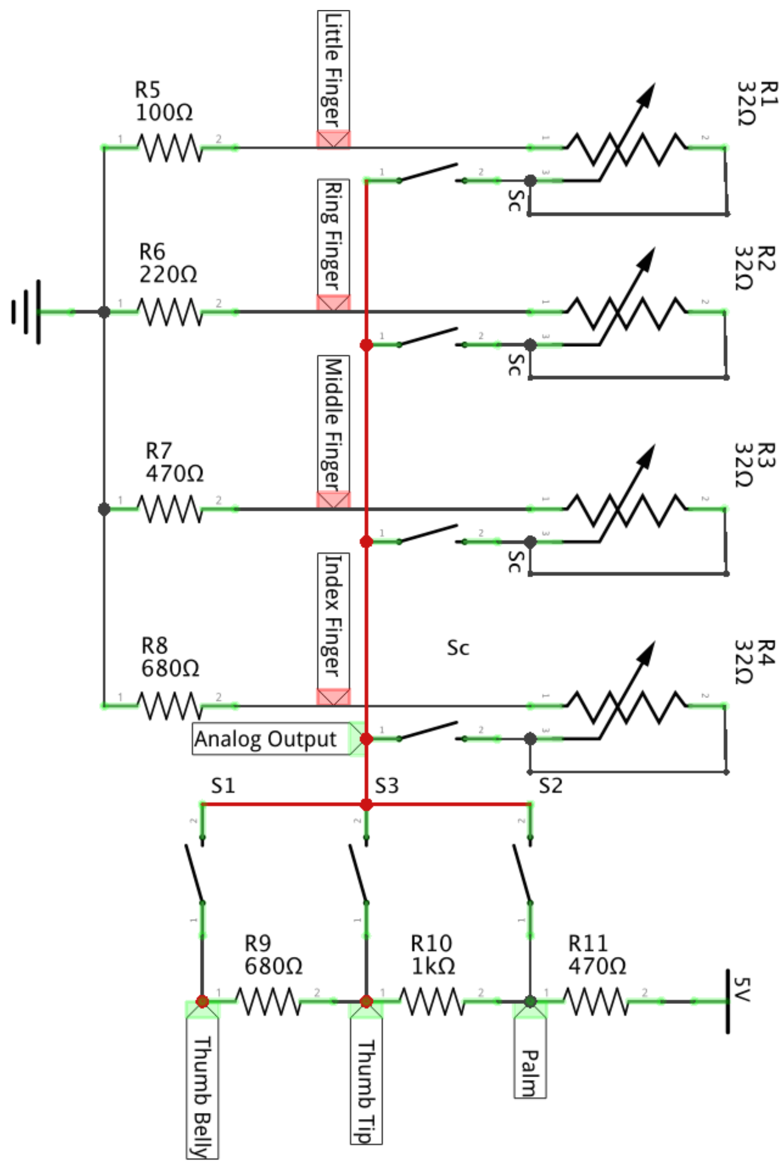


Fig 3.3 Touch Command Circuit

In order to explain the principle clearly, we take the thumb pad activator and little finger as an example. When the thumb pad switch is closed, a new resistor R9 is added in parallel. The final resistance of the little finger would be:

$$R1 + R5 \qquad (3-1)$$

where the value of R1 will be determined by the position on the sensor. For the closed circuit, the resistance would be:

$$R1 + R5 + R9 + R10 + R11 \qquad (3-2)$$

The voltage of the little finger label point on the little finger would be:

$$\frac{V_{IN}R1}{R1 + R5 + R9 + R10 + R11} \qquad (3-3)$$

In this case,

$$\frac{5R1}{R1 + 100 + 680 + 1000 + 470} = \frac{5R1}{R1 + 2250} \qquad (3-4)$$

Therefore, the changing values of R1 determine the touch position on the hand and impact the voltage of the Analog Output point. By measuring the output analog voltage signals, we are able to detect the touch command of different positions on different fingers.

3.3.2 Flex Sensor

The self-resistance of flex sensors can change (increase in this case), when the sensor itself is bent (see Figure 3.4). This property of the sensor supplies a method of measuring the degree of bending in the finger, which is along the back of the finger. Flex sensors are used here for monitoring finger formation.

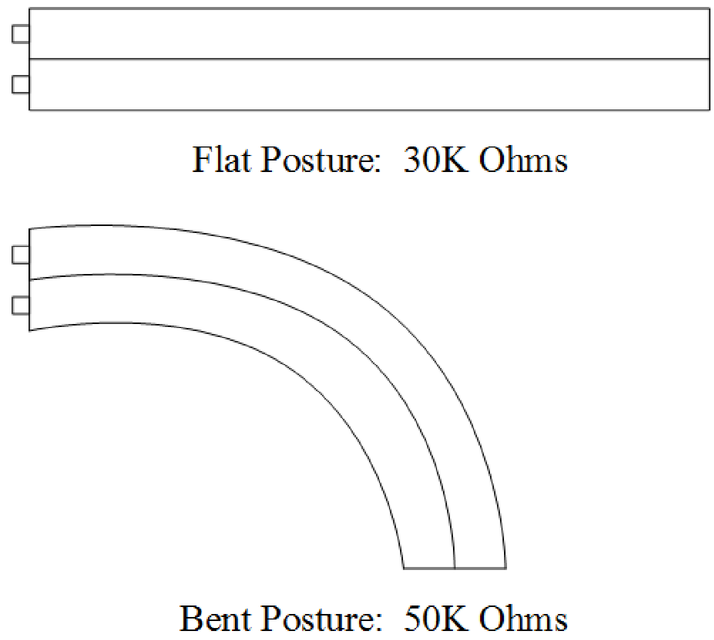


Fig. 3.4 Flex sensor properties

From chapter two, we know that there has already been some research and products that use the flex sensor for similar objectives. We designed and built the glove with similar principles. We use a one sensor per finger setup instead of multiple sensors per finger. Figure 3.5 presents the position of the flex sensors we installed on the glove, with respect to their positions on the hand.

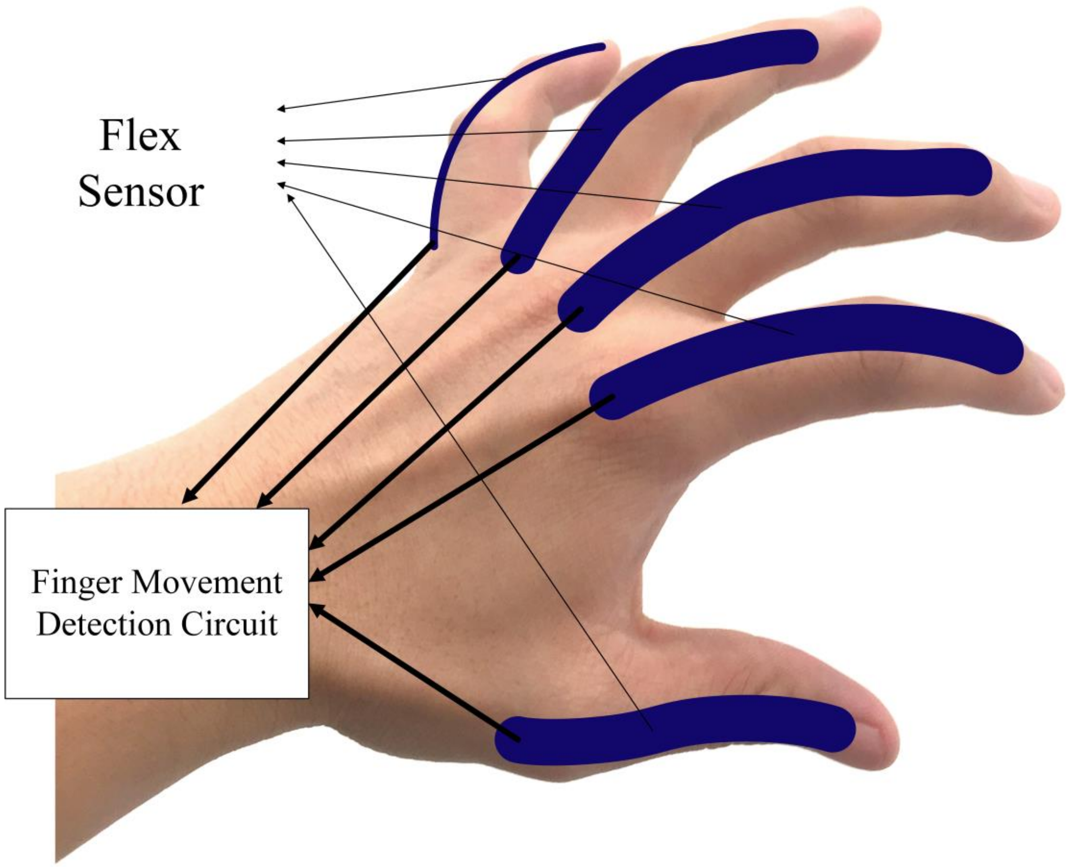


Fig. 3.5 Flex sensor position

With its property of changing resistance according to the bendability, we can build the signal collection circuit. The design of the finger movement detection circuit is shown in Figure 3.6. R1, R3, R5, R7 and R9 are flex sensors and R2, R4, R6, R8 and R10 are fixed resistor connect with each sensor in series as voltage dividers and protection for the circuit. When a sensor is bent or flatten, the resistance of the sensor would change and cause the voltage of the sensor changing. We are able to measure the bent degree by monitoring the voltage of the sensor.

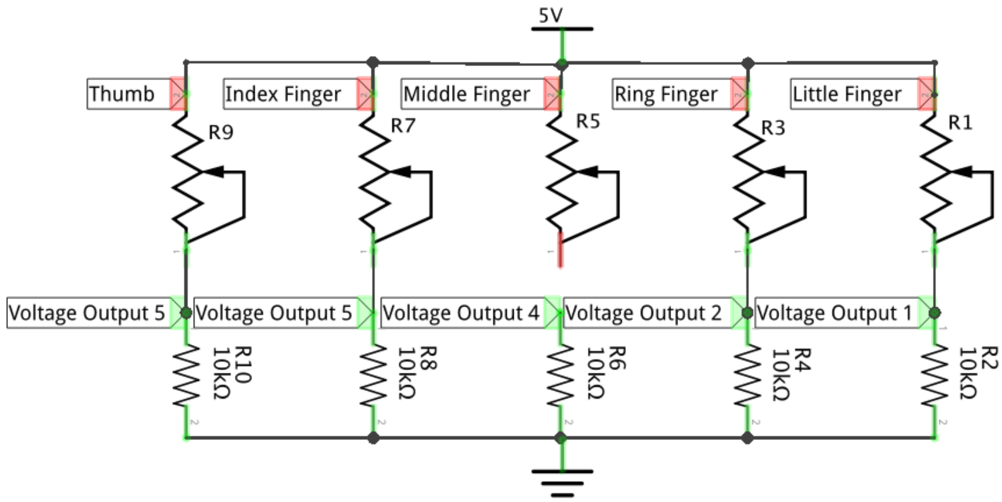


Fig. 3.6 Finger Formation Detection Circuit

To illustrate the principle of finger formation detection clearly, we take the little finger as an example. From the circuit, we know that the total resistance of the little finger circuit is

$$R1 + R2 \qquad (3-5)$$

Therefore, the voltage of the sensor would be:

$$V_{IN}\frac{R1}{R1+R2} \qquad (3-6)$$

where R2 is a fixed resistor with a value of 10K ohm. So we have the expression of the sensor voltage:

$$\frac{5R1}{R1+100000} \qquad (3-7)$$

where R1 will be changed when the sensor is bent by the movement of the little finger, which will change the voltage of the sensor on the little finger.

3.3.3 Motion Sensor

In order to describe a hand gesture, not only the finger formation should be considered, but also a combination with the hand posture. In order to determine hand posture, we used a motion sensor to monitor the angular movement of the hand. The sensor was put on the back of the hand as shown in Figure 3.7. We used a 9-DOF motion sensor, including a 3-axis digital accelerometer, a 3-axis digital gyroscope, and a 3-axis digital compass.

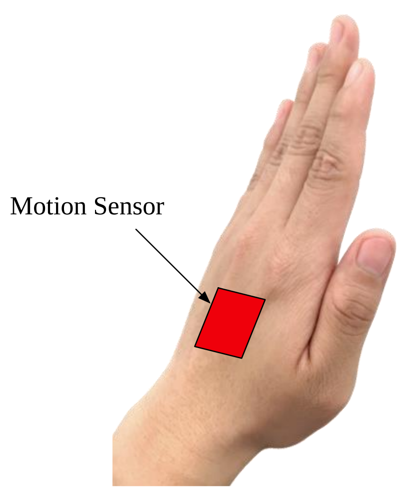


Fig. 3.7 Motion sensor position

Since our detection objective is to recognize static hand gestures, we mainly use the gyroscope and accelerometer to determine hand posture. Nevertheless, because of the mechanism of the sensor, the measurement of rotation around the Z-axis drifts over time. (see Figure 3.8) There are two types of solutions:

- **Estimation algorithm:** By using an estimation algorithm such as the Kalman filter, we can remove the drift phenomenon by using an estimate from previous moment data. Given that the system requires accurate measurement, a Kalman filter will not be accurate after a while.

- **Calibration with other sensors:** In our case, synchronizing the gyroscope with other sensors is a more feasible since there is already a digital compass built into the breakout board, and the result is more reliable since the data is from actual measuring.

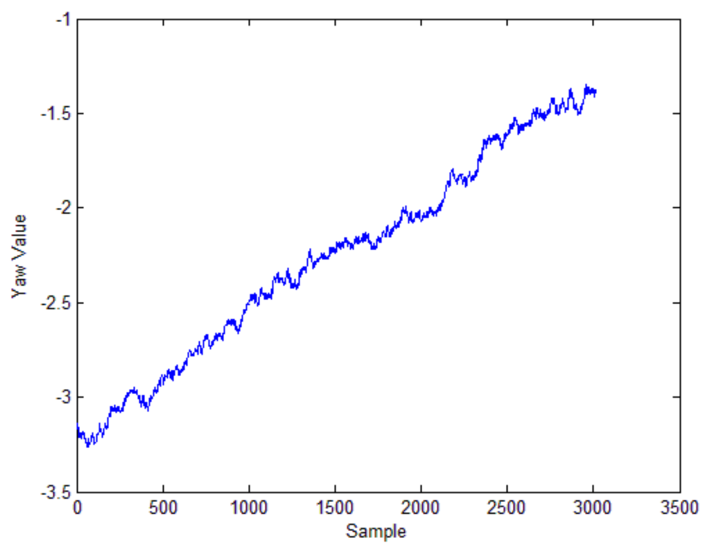


Fig. 3.8 Yaw drift in 2 minutes while the sensor is stable

Figure 3.9 presents our process of calibrating the yaw values. In the beginning, we will have an initialization sequence, which collects the three dimensional initial data from a digital gyroscope and a digital compass and set this specific status as the starting state. After mapping the data from the X-axis of the digital compass to a range of -180˚ to 180 ˚, we were able to fuse the digital compass data to the gyroscope data and solve the drifting problem of the yaw axis. We used a moving average median filter to further ensure the stability of the data: we calculated and saved median values of every third set of data, and the output is the average value of each of the three median values.

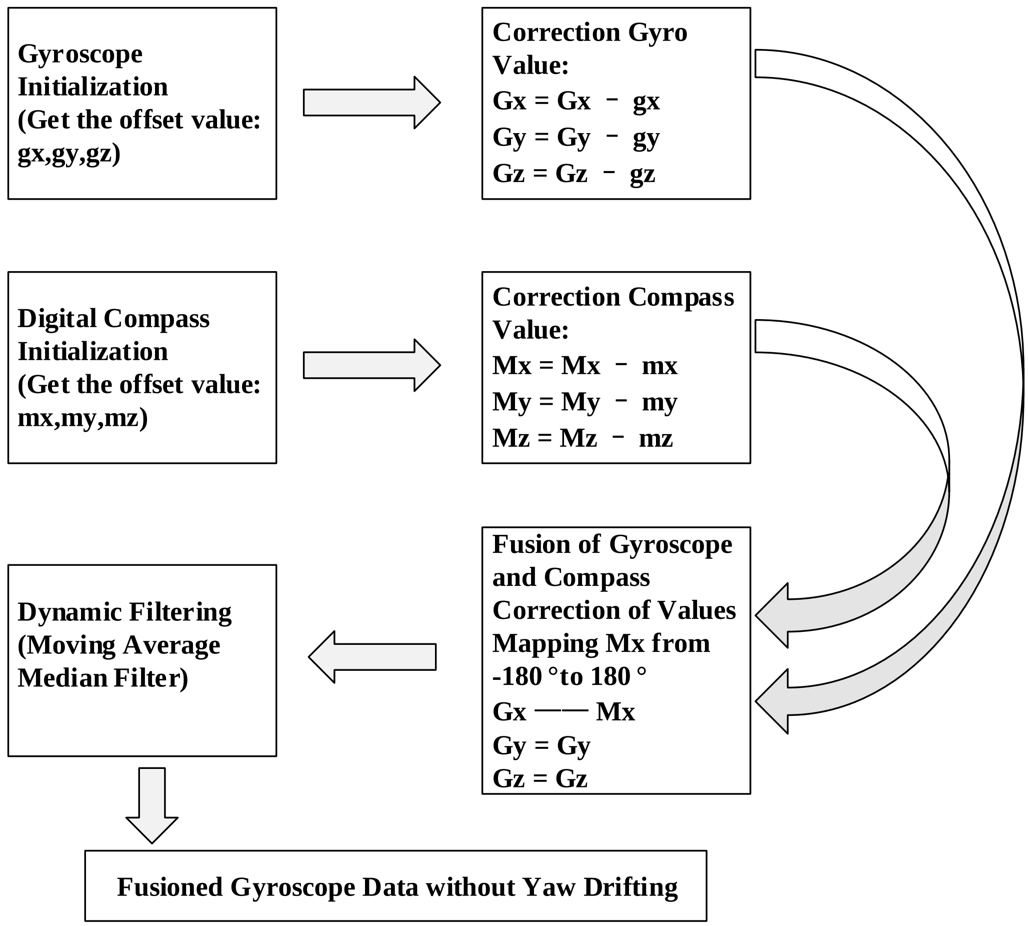


Fig. 3.9 Data fusion of gyroscope and digital compass

The sensor we proposed to use here connects to a microcontroller-based system by an I2C protocol and provides a fast response and reliable data.

3.4 Signal Processing

Along with their circuits, the rheostat, flex and motion sensors transmit the signal to the microprocessor. Since we propose two types of systems in section 3.2, the role of the microcontroller is different for each type. In Type 1 systems, the microcontroller first converts the analog signal into digital forms in order to process it. The microcontroller recognizes the gesture and sends its ID directly to the client. For the Type 2 systems, the microcontroller acts as a hub. After converting the analog signal into its digital equivalent, the microcontroller transmits the signal directly to a connected computing device where the gesture recognition process is executed.

3.4.1 Signal Conversion and Pre-processing

Signal conversion and pre-processing is done by the microcontroller system for both types of systems. Signals from different kinds of sensors require different methods of pre-processing:

- **Rheostat sensor:** Readings from the rheostat sensors on the fingers present different voltages at different touch positions actuated by different activator. We need to map those signals with different magnitudes to pre-defined values in order to make it easier for management and identification.
- **Flex sensor:** We use individual ports to monitor the flex sensors on each finger. However, despite having the same degree of bend, two flex sensors may display different resistances. Besides, the degree of bend in the flex sensors would be different on different fingers. Therefore, we need to unify this data by using remapping:

    - $X = \frac{(x-xl)(U-L)}{xu-xl} + U \qquad (3-8)$

where X is the remapped data, x is the initial data, xl is the lower limit of the initial data, xu is the upper limit of the initial data. U is the upper limit of the remapped data, and L is the lower limit of the remapped data. In our case, we remap the data into 10 levels: from 0 to 9.

- **Motion sensor:** Data from the motion sensor is transmitted by an Inter-Integrated Circuit protocol in the form of a complete data set including gyroscope, accelerometer and digital compass data. After the process of fusion of the gyroscope data with the digital compass as mentioned above, the microcontroller only needs to organize and send the calibrated data to the upper computer.

Finally, the microcontroller packs all of the above into a package. We set up head and end verification to secure the transmission. We also included the length of the package which makes it easier for the upper computer to analyze. An example of a completed package of data would be:

AA 44 0C 01 02 03 04 05 06 07 08 09 0A 0B 0C EA

where AA 44 is the format header of the package. 0C is the length of the contents, which is 12 bytes in this case. The data before EA is the data we sent, which includes 3 bytes of data from the accelerometer, and 3 bytes of fusion gyroscope data; 5 bytes of data of the flex sensors is the contents of the package in hexadecimal. In the end, EA is the carriage return.

In the upper computer, the system receives the package and extracts the content. Then, the data is converted into decimal and saved into an array: savedata for further processing.

3.4.2 Hand Modeling

Similar to the computer-vision-based hand gesture recognition discussed in section 2.2.1, we need to build a model of the hand to transform the gesture into mathematical form. We built the mathematical model of the hand with respect to the data we are able to collect form the group of sensors, and based on this feature, we classified the models into two categories:

Finger model: In chapter two, we mentioned Lien's work [62] for modeling the hand as different dimensions of freedom in the joints. Nevertheless, based on our observation and studying the background knowledge, in most cases, all of the joints on the same finger will bend or straighten at nearly a ratio of 2/3 for DIP and PIP joint angles and a ratio of 1/2 for MCP and PIP joint angles [58], therefore the finger formation can be describe as one degree of flexibility. We propose using, a one degree of freedom angle to represent the degree of finger bend, measured by a flex sensor on the finger (see Figure 3.10.) which can also reduce the cost on redundant sensors. The finger formation is defined as a set of five angle (Δ_1, Δ_2, Δ_3, Δ_4, Δ_5) measurements within 10 levels of bending: 0 being the flat status and 9 being the most curled degree. The algorithm of finger formation recognition will analyze these five degrees.

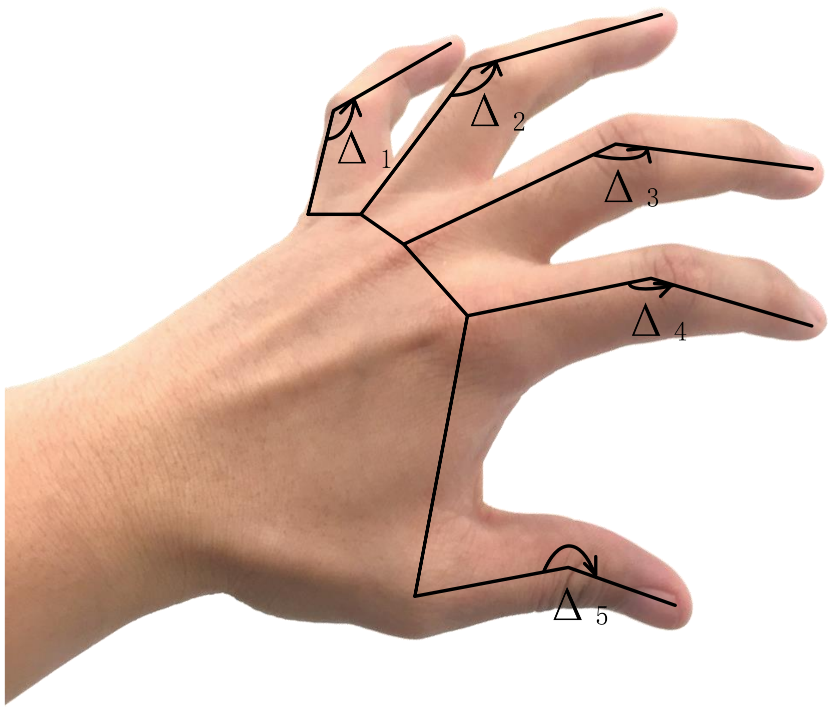


Fig. 3.10 Finger modeling

Hand model: Unlike the lower dimension data of finger model, the hand posture depends more on the dimensions of the data. The rotation of the hand with reference to the initial position determines the hand posture in our research. The data from the gyroscope describing hand posture is three dimensional data that uses yaw, pitch and roll to represent the rotation along the z, y and x axes. In Figure 3.11, we can see that α, β, and γ together represent the hand posture. The blue plane xyz is the initial position. The red plane XYZ is the current hand position. In this case, α is yaw, β is roll and γ is pitch in the definition of static Euler angle. With the assistance of three axis acceleration, the hand model we built here can be used in linear SVM to determine different category of hand postures.

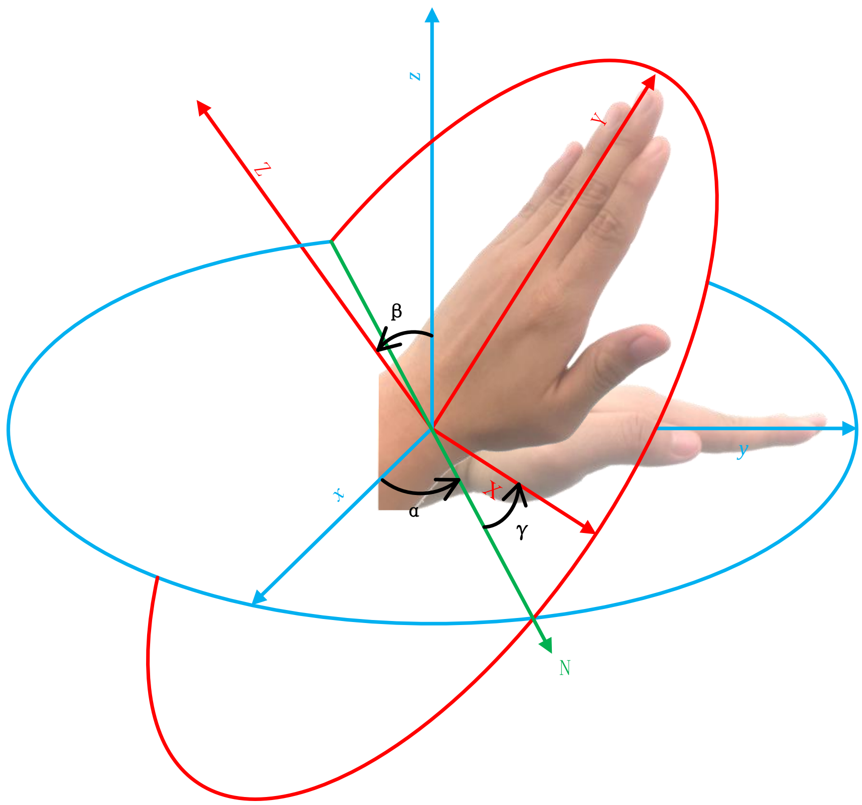


Fig. 3.11 Hand modeling

3.4.3 Gesture Recognition

So far, we have organized all the data to describe the hand gestures to include 12 dimensions of data: one dimension of touch command, flex dimensions of thumb, forefinger, middle finger, ring finger, and pinky finger, as well as three dimensional of rotation data: yaw, pitch, roll and the three dimensional data of the accelerometer, which can be classified into three categories. These categories are touch command, finger formation, and hand posture. We propose using two classification methods to determine the specific hand and finger formation: lookup table and gyroscope. The lookup table method is used for both touch command and finger formation determination, while the linear support vector machine is used to determine the hand posture component.

3.4.3.1 Lookup Table

We use a lookup table to determine the touch command and finger formation because the parameters for the postures of both can be predefined and they are not complex to process. The touch command and finger formations are tagged as a touch command ID or a finger formation ID from the result of the lookup table, while their parameters are combined into a number to search for the corresponding gesture ID. We introduce both categories below:

Touch command: In order to recognize the touch command on the glove, we first test readings from each position with different actuators and record this data. We then build a lookup table with the resulting gesture IDs and corresponding readings. For precision of the system, we repeated the test three times for each reading. The recognition of touch commands for both Type 1 and Type 2 systems is determined by the Algorithm 1.

From touch command recognition algorithm, we can see that the system constantly collects the touch command data from the received data package, and tries to find the reading within the touch command database to get the touch ID. The system then displays the touch position and actuator and/or sends the corresponding command to applications.

```
Algorithm 1 Touch Command Recognition
Requirement: touchcommandID[]
Ensure: TouchID, savedata[11]
touchID ←0;
Start:
switch(savedata[11]){
case 0:{
          touchID←0;
     }
case 1:{
          int j ← savedata[11];
          touchID←touchcommandID[j];
     }
case
…
…
…
case 200:{
          int j ← savedata[11];
          touchID←touchcommandID[j];}
End.
Return touchID
```

Finger formation: We also use a lookup table for finger formation recognition. From the previous section, we know that the finger formation we define here for this system is five degrees of flexibility for each finger. Each finger formation has its own static position for each finger, and by measuring the degree on each finger of the hand position, we are able to determine the gesture. The model of a gesture has range of the degrees of each finger. For example, take the number one in American Sign Language; from Figure 3.12, we know that, except the index finger which is flat, all the other four fingers are flexed, and there is a range in the degree for each finger. The upper limit and lower limit of readings for this gesture in our system are shown in Table 3.1. Note that the upper limit and lower limit will be stored in the finger formation database.

Fig. 3.12 Number one in ASL

Table 3.1 Data of number one in American Sign Language

Finger	Upper Limit	Lower Limit
Little Finger	7	9
Ring Finger	7	9
Middle Finger	7	9
Index Finger	0	2
Thumb Finger	5	8

By implementing Algorithm 2, the system is able to recognize the finger posture according to the database we built. The degree of bending of each finger will be stored in savedata[6] for the little finger, savedata[7] for the ring finger, savedata[8] for the middle finger, savedata[9] for the index finger and savedata[10] for the thumb. The system compares this data with the finger formation database which consists of five 2-dimensional arrays containing the upper limits and lower limits of each gesture for each finger. If any finger formation ID number N fits the entire condition, N is identified as the corresponding finger formation.

In general, we made a finger formation database which is suitable for most people. However, in some circumstances, in order to increase the precision of the system, there would be a tuning process to personalize the gesture for the specific person. In addition, more personalized finger formation could also be set up during this process.

```
Algorithm 2 Finger Formation Recognition

Requirement: N, FingerGestureID[N], LittleLimit[N][2],
RingLimit[N][2], MiddleLimit[N][2], IndexLimit[N][2],
ThumbLimit[N][2]

Ensure: FingerID, savedata[6], savedata[7], savedata[8],
savedata[9], savedata[10]

FingerID ←0;

Start:

for each N, N∈(total support gesture number)

if (

(savedata[6]>=LittleLimit[N][0]&&savedata[6]<=LittleLimi
t[N][1]])&&

(Savedata[7]>=RingLimit[N][0]&&savedata[7]<=RingLimit[N]
[1])&&

(Savedata[8]>=MiddleLimit[N][0]&&savedata[8]<=MiddleLimi
t[N][1])&&

(Savedata[9]>=IndexLimit[N][0]&&savedata[9]<=IndexLimit[
N][1])&&

(Savedata[10]>=ThumbLimit[N][0]&&savedata[10]<=ThumbLimi
t[N][1]))

then

FingerID ← FingerGestureID[N]

else

FingerID ← 0

end for

End.

Return FingerID
```

3.4.3.2 Linear Support Vector Machine

In the beginning of our research, we had implemented a lookup table method for the detection of the static hand posture. However, we found that the precision of this method was not good since it depended heavily on the limit we had set. Besides, a feature of the data to determine gestures is 6 dimensions in total: 3-dimensional data from the gyroscope and 3-dimensional data from the accelerometer which increase the complexity of the tuning process. Therefore, we needed to find a common and easy way to use a classification tool. Machine learning algorithm is the most consistent with these requirements. In this research, we use a Linear Support Vector Machine for the static hand posture recognition.

Support Vector Machines have been widely used in classification, regression, density estimation and clustering as a proven classification tool. Among the Linear SVM and Kernel SVM, we choose Linear SVM for the following reasons []:

1. **Efficiency:** The prediction function of Linear SVM $f(x) = w^T x + b$ is simple. On one hand, since our system is a real time human-computer interaction system, the response time should be considered. On the other hand, for the SVM, when it comes to multiple class classification, the speed of the classification should also be considered. w^T in a Linear SVM prediction function can be pre-calculated, which makes the recognition process efficient, while a non-linear SVM would have a large number of support vectors and cost a long time compared to the Linear SVM method.

2. **Guaranteed replicability:** Non-linear SVM could be over fitting while Linear SVM could already reach an acceptable level of accuracy without the mass calculation as non-linear SVM.

According to the prediction function for multi-class classification of Linear SVM,

$$\boldsymbol{f_y}(\boldsymbol{x}) = \boldsymbol{wx} + \boldsymbol{b} \qquad (3-10)$$

,we know that with the purpose of recognizing hand posture from the data matrix *x*, we first trained the entire supported gesture database by finding the maximum margin of different gesture data:

$$arg\underset{w,\,\xi,\,b}{min}\left\{\frac{1}{2}\left||\boldsymbol{w}|\right|^2 + C\sum_{i=1}^{n}\xi_i\right\} \qquad (3-11)$$

$subject\ to\ \left(for\ any\ i = 1, \ldots n\right)$

$$y_i(\boldsymbol{w}\cdot\boldsymbol{x_i} + b) \geq 1 - \xi_i\,,\ i = 1,\ \ldots,\ n\ (\xi_i \geq 0) \qquad (3-12)$$

And we get a matrix *w* for further recognition.

In the recognition process, the total number of supported gestures is already known from the gesture database. Each hand posture has its own ID which is also predefined by the gesture database. Usually, we tag them with a natural number sequence. The system keeps updating the package of data from sensor, and processes that data in the following sequence:

Step 1: The system insures each element of an array f is zero.

Step 2: For each element in array f, we apply the prediction function with the parameters from the hand gesture database and variables from the received “savedata” array.

Step 3: The system finds the element in array f with the largest value and tags the gesture ID as the index of the exact array.

Step 4: Finally, this method returns the hand gesture ID “HandID”.

```
Algorithm 3 Hand posture Recognition

Requirement: N, HandPostureDatabase[N][7],

Ensure: HandID, savedata[0], savedata[1], savedata[2],
savedata[3], savedata[4], savedata[5], f[N]

HandID ←0

for each N, N ∈ (total support posutre number)

f[N]←0

end for

Start:

for each N, N ∈ (total support gesture number)

f[N]←HandPostureDatabase[N][0]*savedata[0]+
HandPostureDatabase [N][1]*savedata[1]+
HandPostureDatabase [N][2]*savedata[2]+
HandPostureDatabase [N][3]*savedata[3]+
HandPostureDatabase [N][4]*savedata[4]+
HandPostureDatabase [N][5]

end for

for each N-1, N ∈ (total support gesture number)

if (f[N]>f[N+1]) then

max←f[N]

HandID←N

else
max←f[N+1]

HandID←N+1

end if

end for

Return HandID

end
```

3.5 Client (Host Computer)

The client or the host computer of the proposed system varies for the purpose of the system. When we need to utilize SVM for the determination of hand posture, the client is responsible for both training for the gestures and recognizing them (Type 2 system). However, if training is necessary, we just apply the recognition part to the lower computer: microcontroller (Type 1 system).

We can connect the system to a computer as a replacement for traditional input methods such as a mouse and a keyboard. It can also replace a joystick and provides a more realistic gaming interaction experience. As a 3D virtual interaction device, the system can be deployed in virtual design, assembly, and manufacturing by combining gesture commands and voice commands. If connected with a mobile device such as a smartphone, it can help others to understand the user's gesture meaning.

The connection method between the system and client could also be different. A wired connection with the computer provides a secured transmission of the signal. Wireless connections such as Bluetooth or ZigBee [59][60] allow users to experience the freedom, ease and the convenience of gesture-based interactions.

3.6 Summary

We proposed a multimodal data glove system as a solution for improving the drawbacks of the current hand gesture based HCI approaches. It can recognize more gestures, low cost and ease of use. Signal acquisition part is the first part of the system which includes three kinds of sensors, they are resistance rheostat sensors to detect the touch positon on fingers and flex sensors to measure the degree of the fingers were bent. A motion sensor to monitor the hand posture. The signal acquisition has also been built for these sensors. The well processed data will be sent to higher devices for recognition. We implement two approaches for the gesture determination. Lookup table aims to deal with the gesture kind whose data is not complex, while linear SVM we used here is to help with determining hand posture since total of 6 dimension of data judges the hand altitude. Client has also been discussed to discover the application of the system.

Chapter 4 Implementation and Results

4.1 Hardware Implementation

The hardware implementation has 3 parts: sensors and their setup, circuits responsible for signal acquisition including the glove's embedded microcontroller, the computer connected to it and the communication between the upper computer and the lower computer. The hardware implementation ensures the signal collection from sensors as well as the transmission of data to the client.

4.1.1 Sensor Setup

In chapter 3, we mentioned that three kinds of sensors are mainly used in our system: resistance rheostat sensors, flex sensors and a motion sensors. Due to cost considerations, we tried to utilize the most accessible and inexpensive sensors.

There is already a product called the Peregrine Glove that uses embedded resistance rheostat sensors on the fingers. We use its replacement glove (cost under 50 dollars) for its sensors and we will install other sensors onto this glove. There are three sizes of this product to fit different sizes of hands. In order to utilize this glove, we need to first conclude how the sensors on the glove are connected. After doing the test, we summarized the role of each pin for the glove shown in Figure 4.1. We re-soldered the circuit board and left ports for ease of replacing cables for different sizes. Ports for motion sensors have also been left for replacements. Sensors on the glove are connected to the circuit board according to the design in Figure 3.3.

After connecting the sensors, we recorded the readings for different positions with different actuators to build a touch command database.

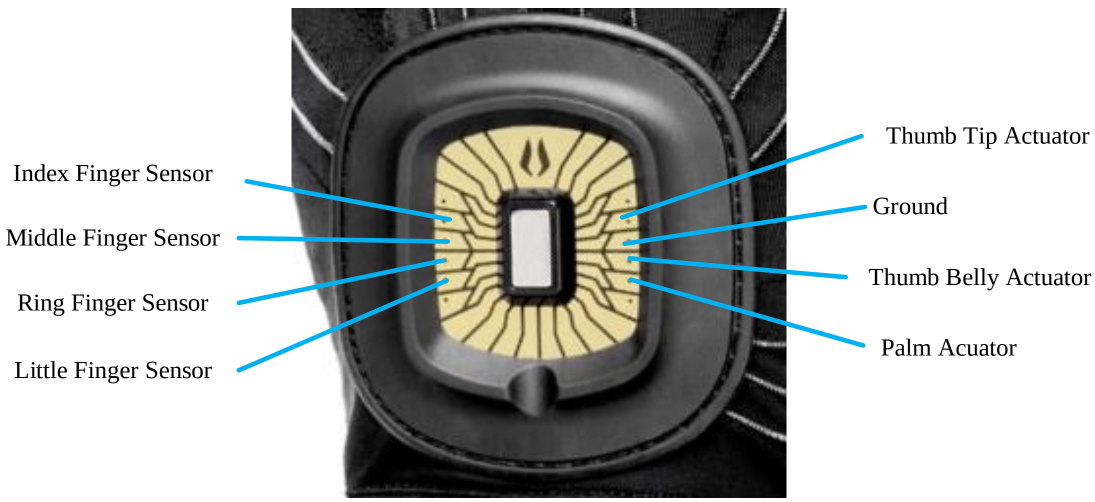


Fig. 4.1 The function of pins on the Peregrine Glove

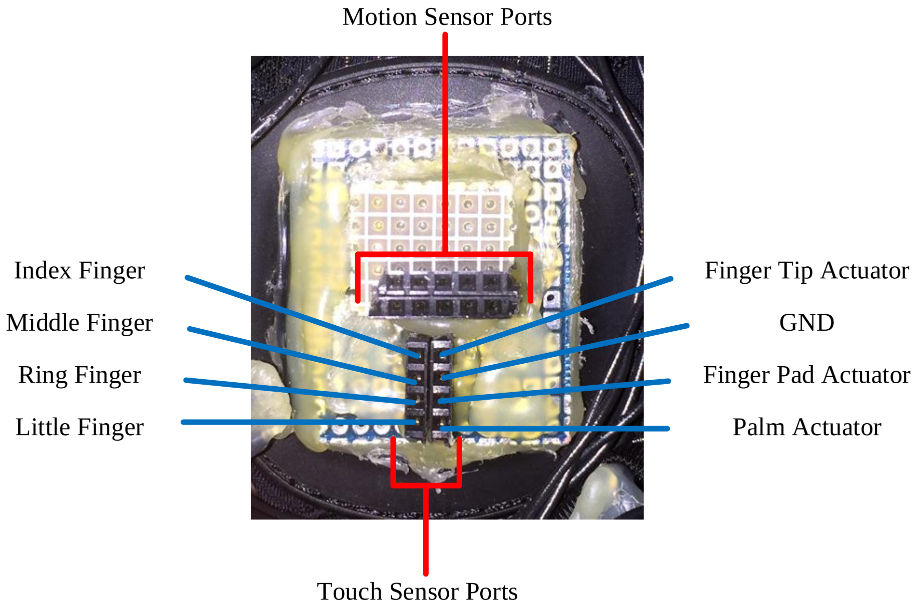


Fig 4.2 Re-soldered circuits on the Peregrine Glove

A feedback actuator was placed in the wrist band in order to avoid interference with the motion sensor.

For flex sensors, we used a 2.2 inch flex sensor (Model Number: SEN-10264) from Spectra Symbol Company. The sensor is soft, accurate and is able to bend over 180 degrees. Flex sensors were attached to the back of each finger and an additional protection layer was adhered (Seen in figure 4.3).

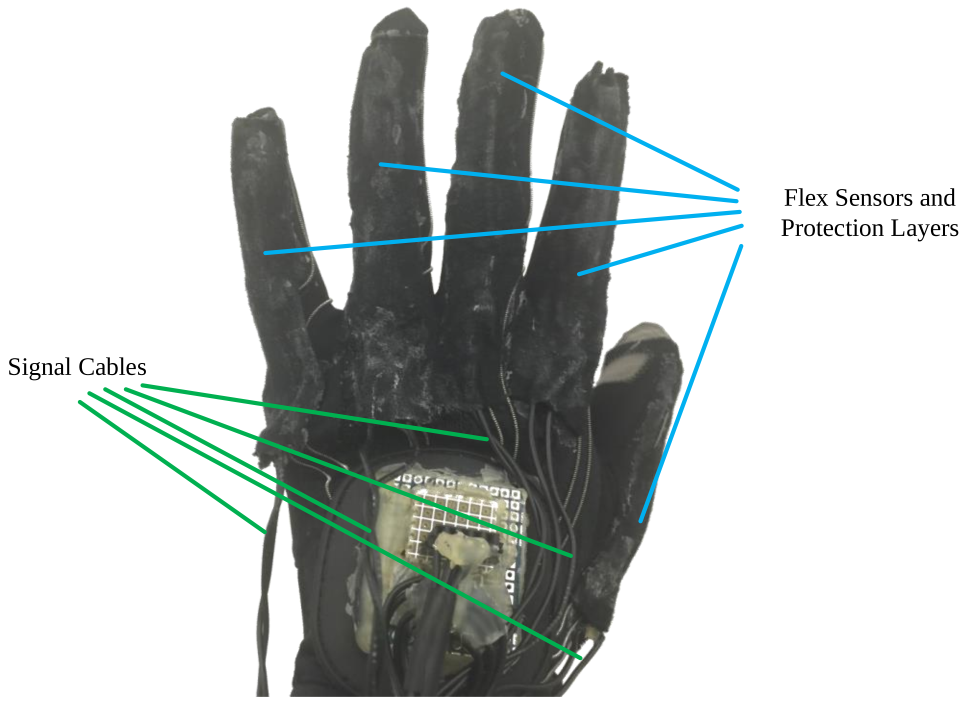


Fig. 4.3 Flex Sensor Implementation

The output produced by the flex sensors differs depending on the finger they are attached to due to the difference in overall length and length between joints of each finger. As a consequence, a tuning process for the flex sensors should be done before using the system. Table 4.1 presents an example of test readings for the developer based on a small size glove. The lower limit was recorded when all fingers were in a flat position, while the upper limits were recorded when the fingers reached their maximum degree of bending. By applying a quantization formula, the reading range of each sensor will be quantized from 0 to 9.

Table 4.1 Flex Sensor Test Result

Finger	Lower Limit	Upper Limit
Little Finger	776	894
Ring Finger	784	914
Middle Finger	760	910
Index Finger	782	915
Thumb Finger	731	795

We selected a 9 DOF motion sensor from Junyue Intelligence Control Company [61] with an accelerometer, gyroscope, digital compass and built-in signal filter. The operating voltage is from 3V to 5V. Two types of connections are supported: serial port with a serial rate from 2400bps to 912500bps and an IIC protocol at 400Kbps. In our system, we used the IIC type to connect the sensor (seen in Figure 4.4).

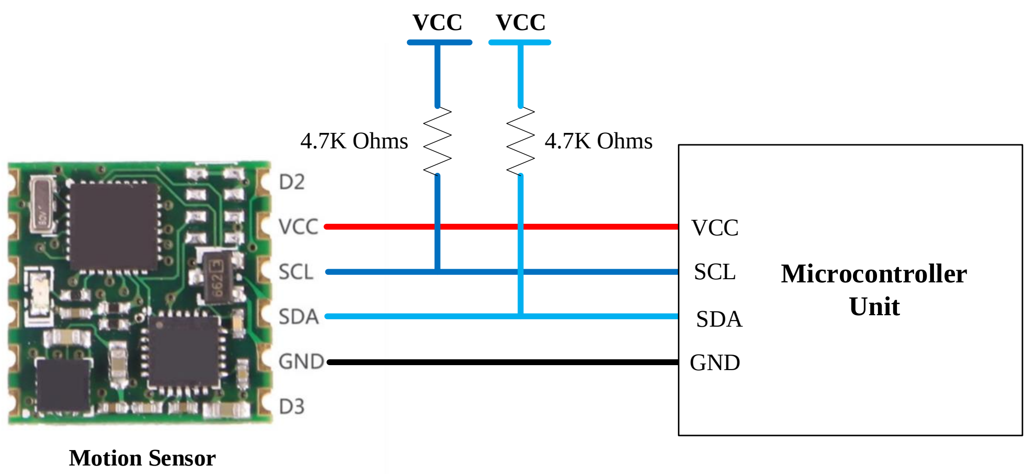


Fig. 4.4 Connection of Motion Sensor

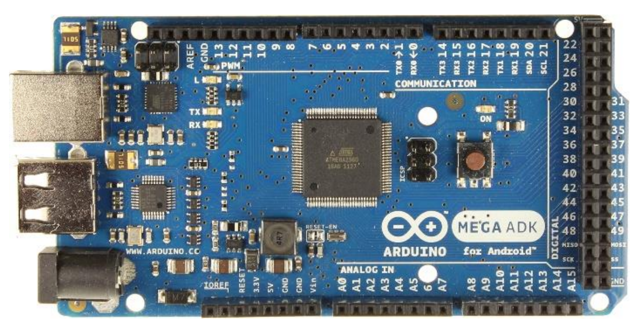


Fig. 4.5 Arduino Mega ADK

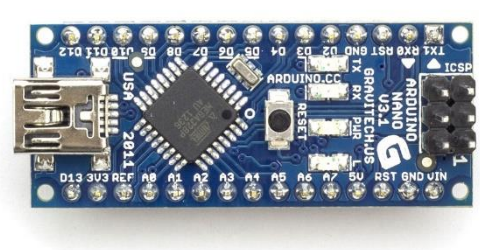


Fig. 4.6 Arduino Nano

For our prototype, we used an Arduino microcontroller as our embedded microcontroller. It provided both analog and digital input and output ports. It is an open source platform using the C language for programming. We built two types of prototypes. The wired version used an Arduino Mega (Seen in Figure 4.5) for its adequate ports and powerful computing power. We used an Arduino Nano (Seen in Figure 4.6) to build the wireless version since its size could minimize the size and weight of the glove system.

4.1.2 Signal Acquisition Circuit Implementation

Sensors were set up well for signal acquisition. By connecting sensors to the signal acquisition circuits and by connecting the outputs of the circuits to a microcontroller unit, the physical displacement or rotation of the fingers and hands as well as the touch command could be transformed into analog electric signals. We connected all sensors to a signal acquisition board (Seen in Figure 4.7 (a) for the wired version and (b) for the wireless version). The wired version board can be divided into four parts: a signal acquisition circuit for the flex sensors, touch sensors, motion sensors as well as haptic feedback ports and a connection port to the microcontroller. The wireless version is designed for mobile applications. Its microcontroller was installed with the circuit board and used Bluetooth to communicate with the upper computer. A multiplexer breakout board was used here to extend the I/O ports of the microcontroller.

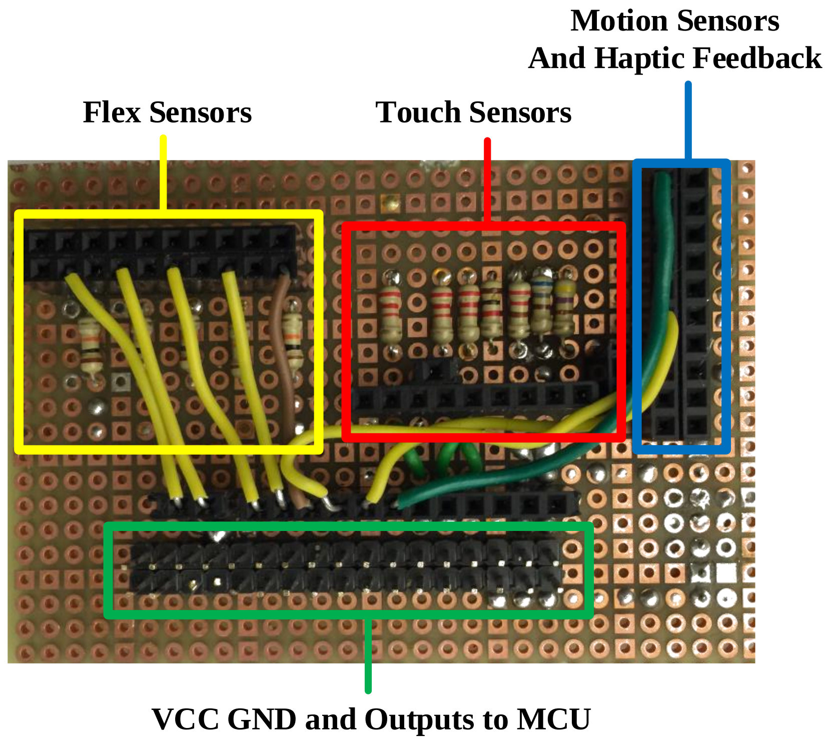


Fig. 4.7 (a) Wired version signal acquisition board

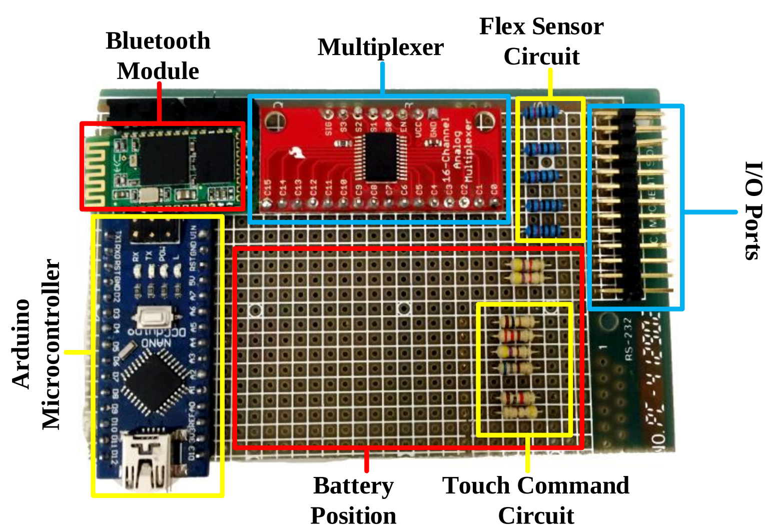


Fig. 4.7(b) Wireless version signal acquisition board

We defined the cable pins according to Figure 4.8 (a) for the wired version and 4.8 (b) for the wireless version.

0	1	2	3	4	5	6	7
N/A	N/A	Flex Sensor Outputs					SDA
8	9	10	11	12	13	14	15
SCL	Haptic Feedback	Touch Command Outputs			5V	GND	3.3V

Figure 4.8 (a) Wired version cable pin definition

1	2	3	4	5	6	7	8	9	10	11	12	13
Motion Sensor I/O and Power				Touch Command Sensor Inputs								N/A
14	15	16	17	18	19	20	21	22	23	24	25	26
N/A	N/A	N/A	Flex Sensor Inputs									

Figure 4.8 (b) Wireless version able pin definition

4.1.3 Communication

The system supports both wired and wireless communication methods. Wired communication between the upper computer and lower computer used a USB virtual serial port communication protocol. The serial rate was 56700 bps which provided both a guarantee of transmission speed and reliability. We used a Bluetooth version 2.0

board (Model Number: HC-06) from the Guangzhou Huicheng Information Technology Company [62] as our wireless communication solution with a working frequency of 2.4 GHz ISM, a modulation mode of GFSK and a maximum transmission power of 4dBm. The module connects to the serial communication ports of the microcontroller unit (Seen in Figure 4.9). The Bluetooth board is a slave and the client is the master. When they are connected, they work under a serial port transmission protocol.

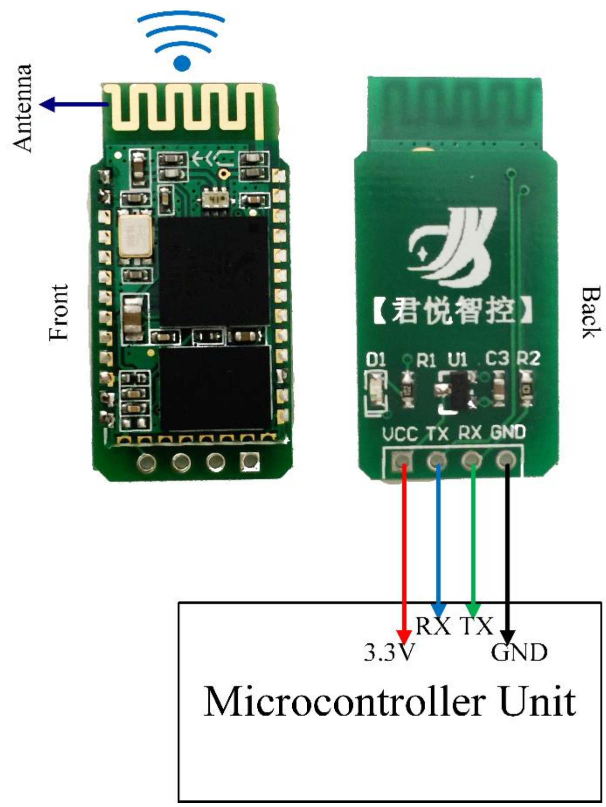


Fig. 4.9 Bluetooth module and its connection

After implementing the sensors and circuits, the whole hardware part of the system is complete. The wearing of the system is shown in Figure 4.10 (a) and (b).

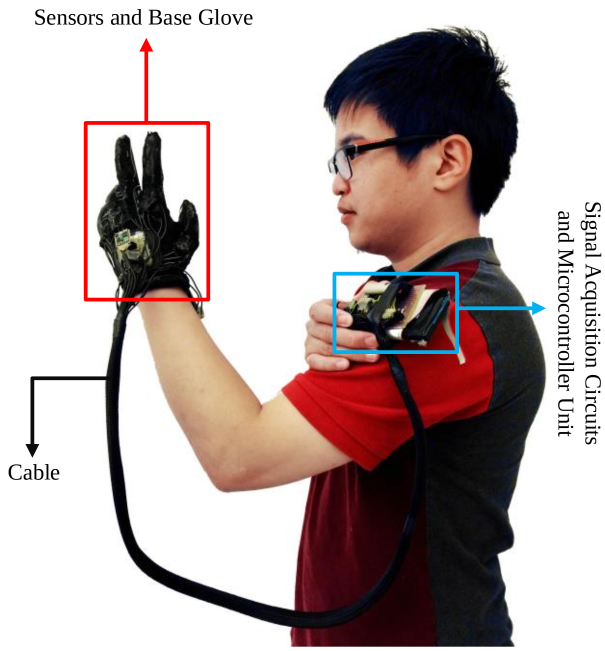


Fig 4.10 (a) System hardware on the user (Wired edition)

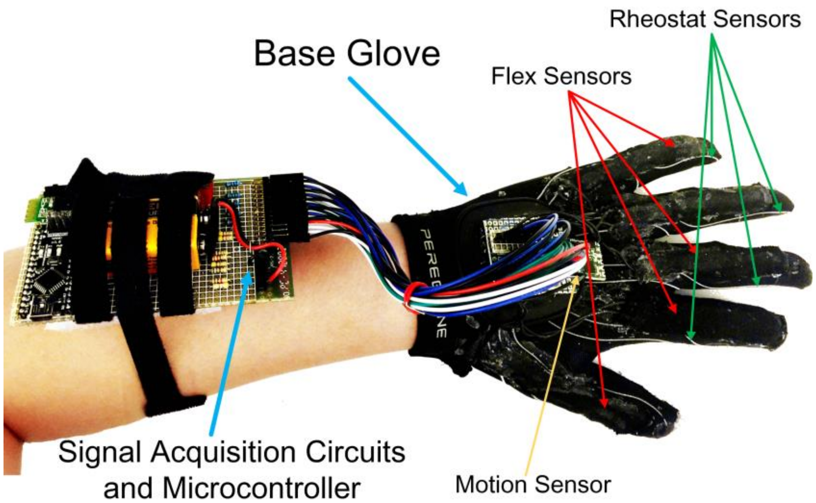


Fig 4.10 (b) System hardware on the user (Wireless edition)

4.1.4 Upper Computer

In order to reduce the impact of the performance from the upper computer, high-end configurations of upper computers were used here for implementation and evaluation. The multimodal data glove system implementation was done with the following upper computers and their software environments:

- **Desktop Computer**: This desktop computer was installed with one Intel(R) Core(TM) i7-4790K processor, 16GB 1600MHz memory and one NVIDIA GeForce GTX-980 graphics card. The operating system was Windows 8.1 Pro 64-bit edition.
- **Laptop Computer**: An Apple MacBook Pro (Retina, 15-inch, Late 2013) composed of an Intel(R) Core(TM) i7-4960HQ processor, 16GB 1600MHz memory, and an NVIDIA GeForce GT 750M graphics card. The operating system was Windows 8.1 Pro 64-bit edition.

To summarize, the cost of hardware for the prototype was as follows:

Table 4.2 Cost of the hardware (In US dollars)

Device or sensor	Rheostat sensor	Flex sensor	Motion sensor	MCU	Bluetooth module	Others (wire, board etc.)
Cost	$49.95 (The Peregrine Glove)	$\$7.95 \times 5 = \$39.75$	$15	$2	4$	10$

The total cost of the wireless version data glove we implemented here was about USD $120. Compared to other expensive data gloves, we successfully reduced the cost to 1/4 of the previously cheapest one (over USD $500). The production cost can be reduced further by purchasing components in a large quantity.

4.2 Software Implementation

The software implementation has two parts: data acquisition and organization on the lower computer and signal processing and function implementation on the glove's embedded microcontroller.

4.2.1 Data Organization and Transmission

A program for the Arduino microcontroller was designed to ensure data acquisition and organization. This program was written in the C language in an Arduino IDE environment. In the initialization sequence, it sets up the serial rate for the communication with the upper computers or the communication with the Bluetooth modules, as well as activates and calibrates the motion sensor. Signals from the digital and analog ports of the board were first filtered and then mapped and organized. We used a moving average median filter which takes the average value of the median values from three moving groups' data from each sensors. Finally, the system packs the entire package with a format header, length of the package, the content of the package and the carriage return.

4.2.2 Gesture Recognition

The gesture recognition is done in the lower computer in type one of the system and in the upper computer in type two of the system. If the user just requires simple finger recognition and hand gestures without training, type one is suitable. However, those who want to maximally exploit the potential of the system can use type two as a solution.

For a type one system, the determination process will be implemented by the C language in the Arduino IDE. For the type two system, the upper computer with its powerful capability will customize the gesture model for specific users and deal with the complex task of the recognition process.

4.2.2.1 Training

The training process is not only for linear SVM approaches; it can also sometimes be implemented for a low tolerance of failure recognition rate for finger recognition. Touch commands, on the other hand, do not need training or tuning since the position on the sensor is in an absolute position, and the user just needs to stimulate the correct positions on the fingers.

- **Finger formation training:** Users present the prompted finger formations for analysis and record the upper limit and lower limit of the readings from the different sensors on different fingers in order to build a properly customized finger formations database. In order to ensure the accuracy of the model database, a minimum of 3 trainings should be processed for each individual gesture. Figure

4.12 demonstrates the result of the "number one finger formation". As seen in the figure, it is not hard to determine the limit of each feature.

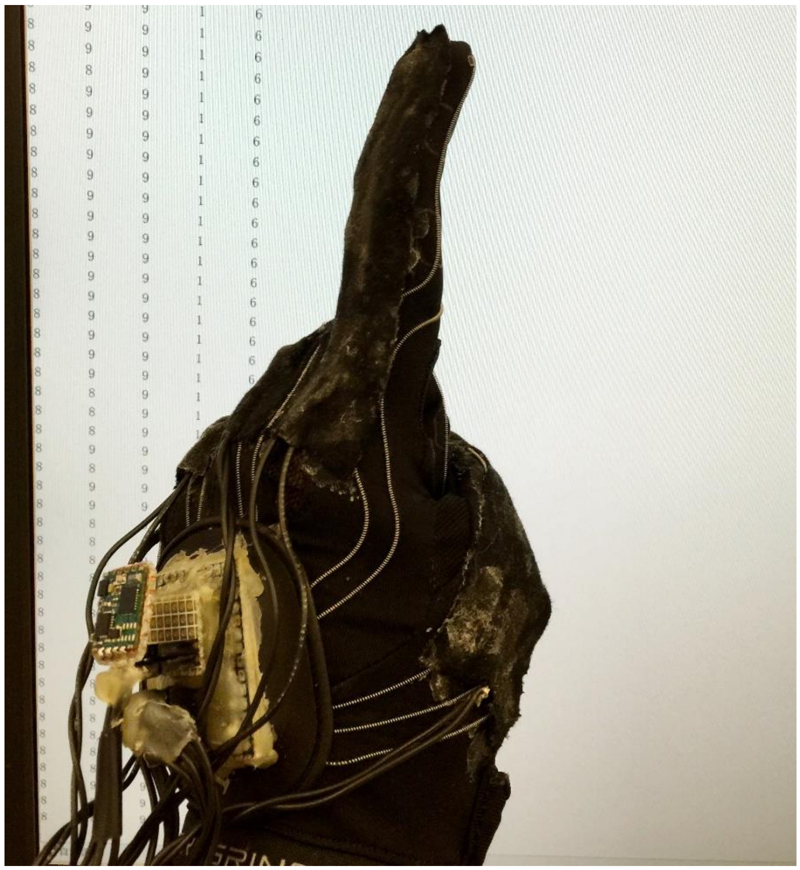


Fig 4.11 Finger formation training

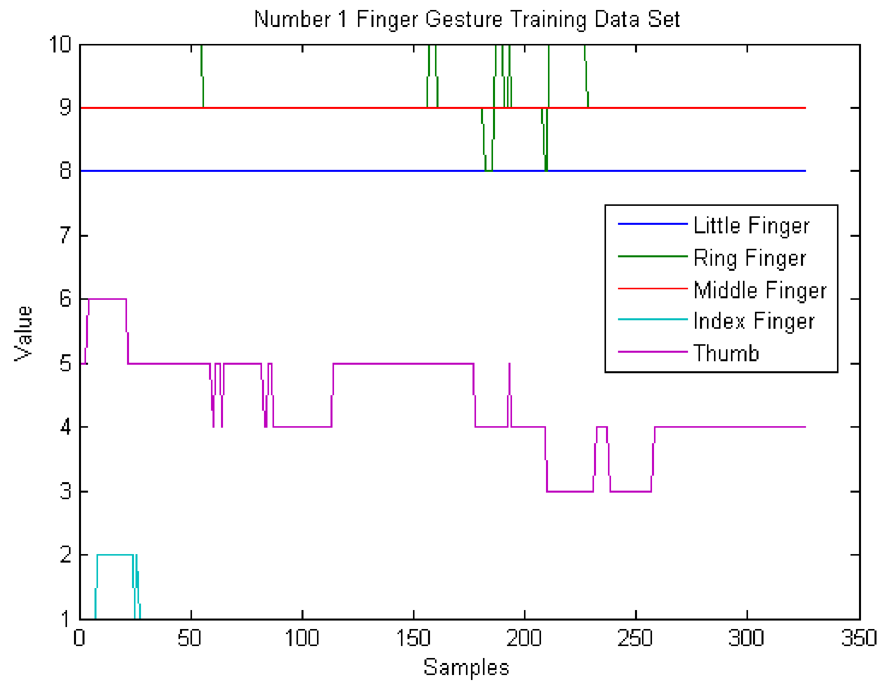


Fig 4.12 “Number one finger formation” training result

- **Hand altitude training:** Since linear SVM is a mature approach, the Liblinear Library from the Taiwan National University was implemented in the system for gesture model training. The required hand altitudes were presented and the data from 3 dimensions of the gyroscope and 3 dimensions of the accelerometer were recorded. As per the Liblinear Library requirements, the data set for training should be in proper form (Seen in Figure 4.13). We made an Excel file with macro commands to transform the regular matrix of the data into the required form for the Liblinear Library. In the end, by using the method from the Liblinear Library in a Matlab environment, we got the hand posture gesture model, which is a matrix of **w** and **b**, to be used in the prediction function of the linear SVM. Figure 4.14 shows the training results of matrix **w**, where the first six columns would be **w** and the last column of the matrix is **b**.

1 1: 90 2:100 3:34 4:23 5:75 6:10

2 1: 4 2:130 3:55 4:132 5:20 6:10

Class Feature Label Value of Feature

Fig. 4.13 Training Data Set of Linear SVM

model.w <10x7 double>

	1	2	3	4	5	6	7
1	-0.0700	-0.0258	0.0119	0.1037	0.1722	-0.0363	3.1160e-04
2	0.0234	-0.0124	0.0017	-0.0118	-0.0308	-0.0365	-1.7788e-04
3	-0.2656	0.0662	0.0104	0.1209	0.3307	0.1681	-8.3352e-05
4	0.0844	-0.1872	-0.0040	-0.0694	0.0645	0.0908	-7.3231e-04
5	-0.0031	-0.0306	-0.0153	-0.0640	-0.0103	0.1318	-6.1277e-04
6	-0.0251	0.0631	-0.0351	-0.0619	-0.0268	0.0151	-1.0090e-04
7	-0.0272	0.0367	0.0297	-0.0571	-0.0134	-0.0395	-3.2887e-04
8	-0.0390	0.0351	-0.0089	-0.0217	0.1454	-0.1079	-2.2813e-06
9	0.1638	-0.2620	0.0107	-0.0537	-0.2372	0.2278	6.7267e-04
10	-0.0260	0.0311	-0.0050	0.0771	-0.0568	-0.0257	8.1522e-04

Fig. 4.14 Trained hand posture model

4.2.2.2 Recognition

After getting the trained models of both finger formations and hand postures, the recognition program reads those databases and recognizes finger formations and hand postures according to the different algorithms we mentioned in Chapter 3. Finger formation is determined through a lookup table to match the input data with different upper and lower limits from the finger formation database. Hand posture is determined by finding the maximum value of each prediction function of different classes. Finally, the result is output as three kinds of gesture ID: a touch command ID, a finer gesture ID and a hand posture ID.

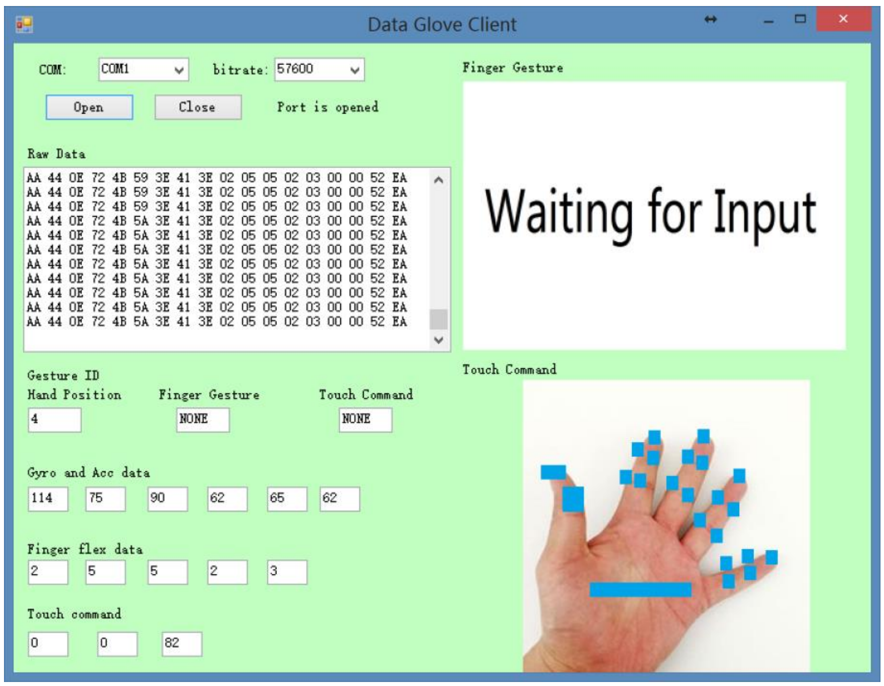


Fig. 4.15 User interface of the system

4.3 Result (Supported Gestures)

A simple user interface was developed to display the detected hand posture, touch command and finger formation after a gesture is performed by a user (Seen in Figure 4.15). This interface is used to perform the objective evaluation of the system. The application also shows the decimal data of the different sensors. The finger formation ID is not only shown by numbers, but also graphically in the upper right panel.

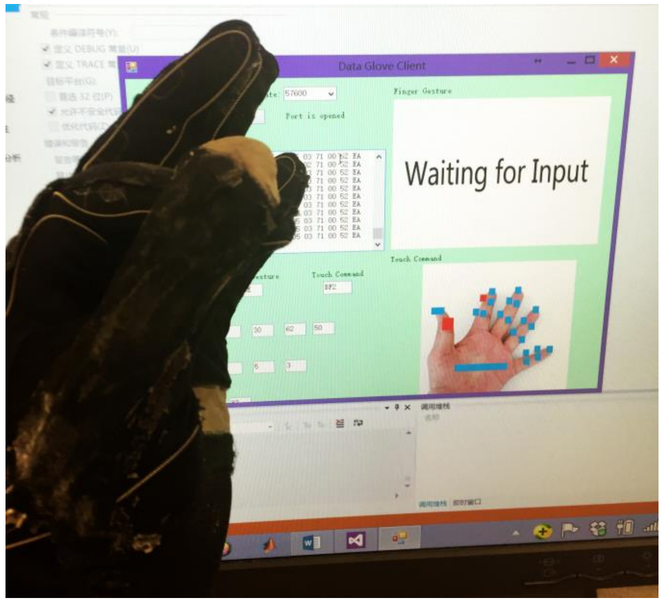


Fig. 4.16 Touch command recognition

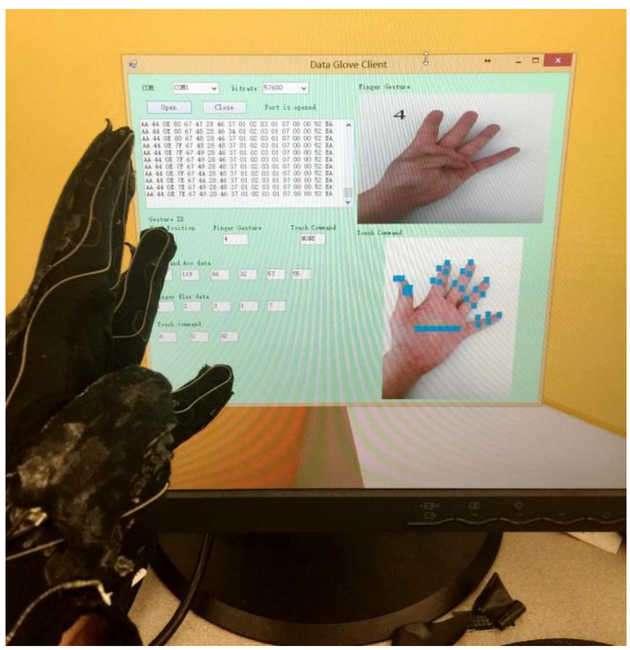


Fig. 4.17 Finger formation recognition

When a touch command is detected, the corresponding actuator on the thumb or palm and the stimulated position is read. If the predefined finger formation is detected, a corresponding photo of that gesture is also displayed.

For hand posture, we used both ID and a 3D visualization program to present the result. This visualization can achieve real-time synchronization between the hand and the 3D model. (Seen in Figure 4.18)

Fig. 4.18 3D visualization of hand posture

By implementing the hardware and software of the system, the multimodal data glove system can support the following command or gestures:

- **Touch command:** Two actuators on the thumb, one on the palm, and 4 positions on each of the other 4 fingers provide over 30 different touch commands.

- **Finger formation:** 18 kinds of finger formations can be determined (Seen in Figure 4.19).
- **Hand posture:** 10 well-trained static hand postures are supported by the system. (See Figure 4.20; the arrow is along the first dorsal interosseous muscle.)

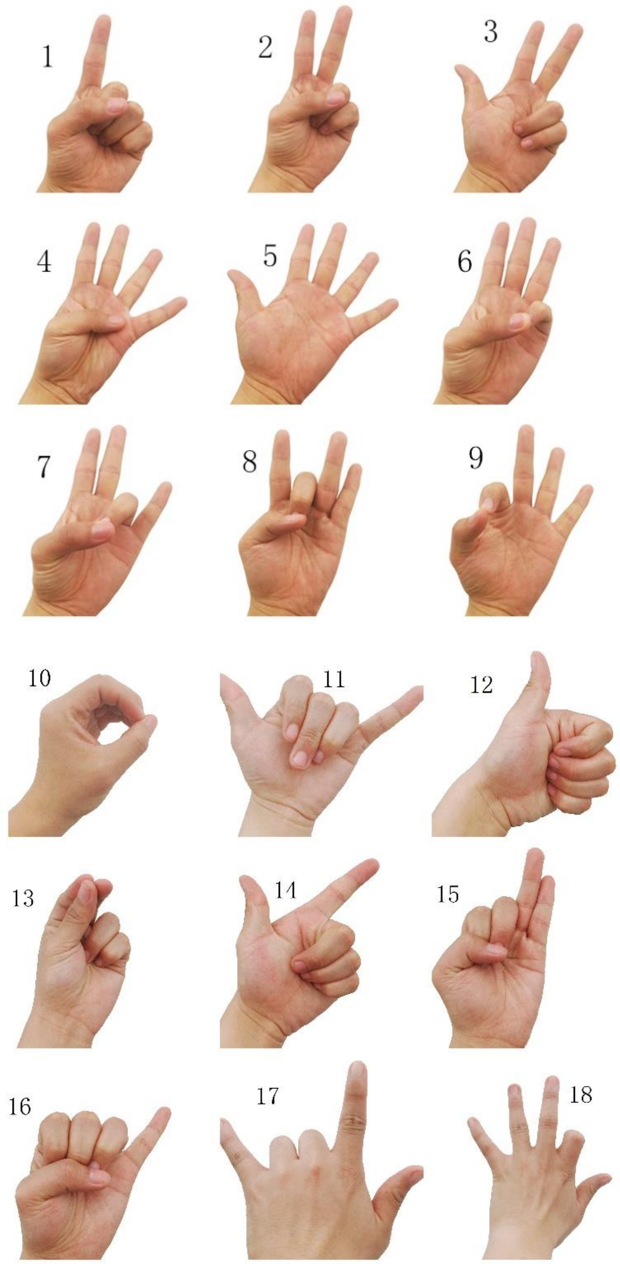
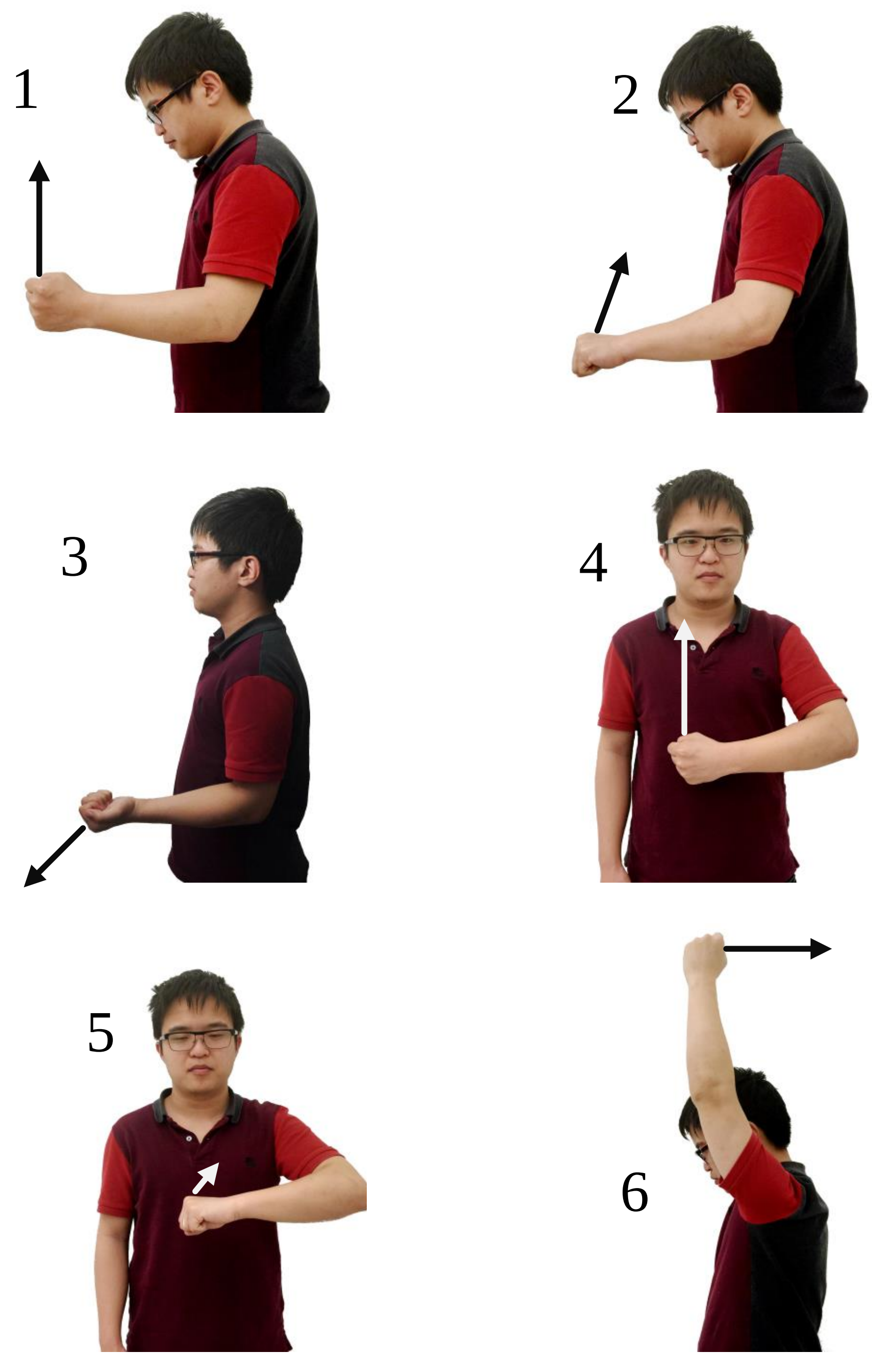
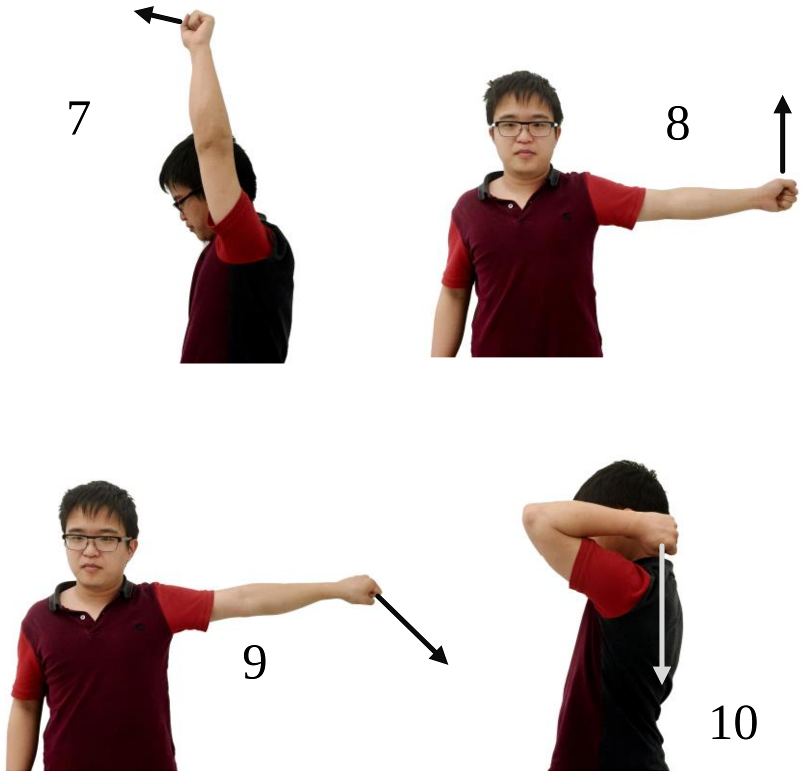


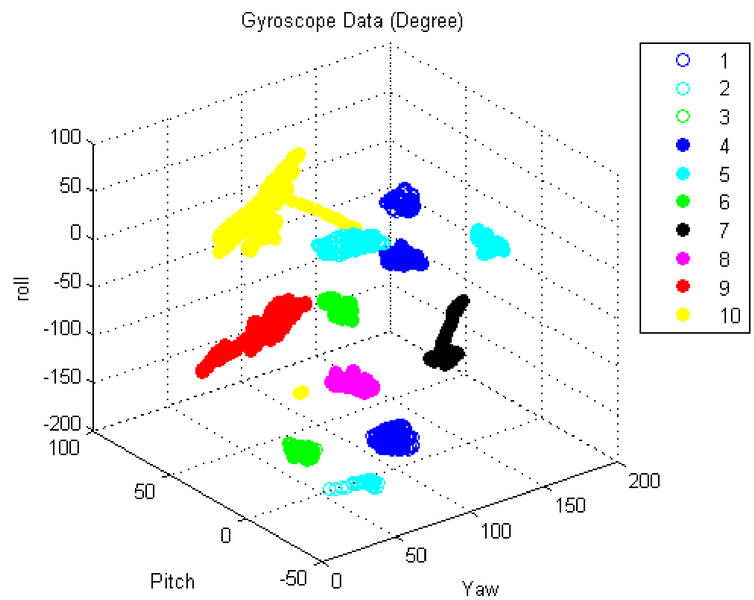
Fig 4.19 Supported finger formations and their ID



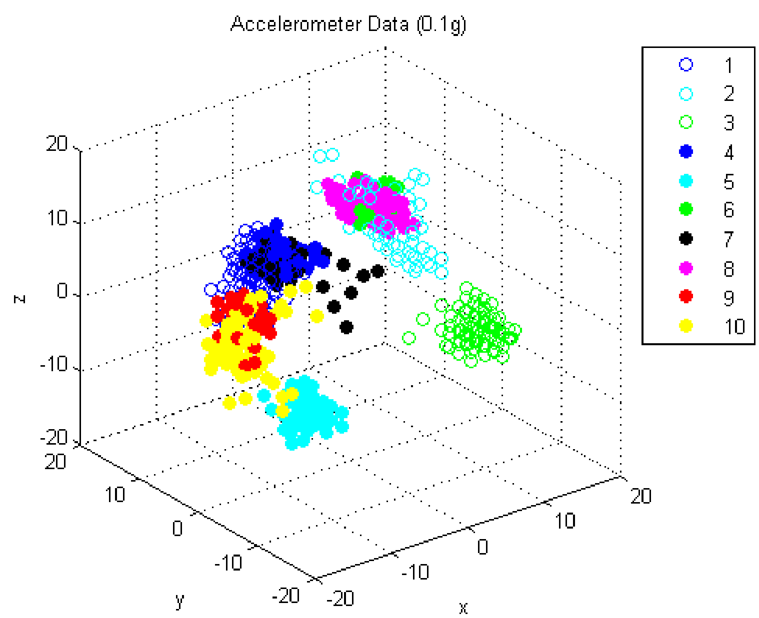
4.20 (a) Supported hand gestures and their ID



4.20 (b) Supported hand gestures and their ID



4.20 (c) Data set for building hand gestures



4.20 (d) Data set for building hand gestures

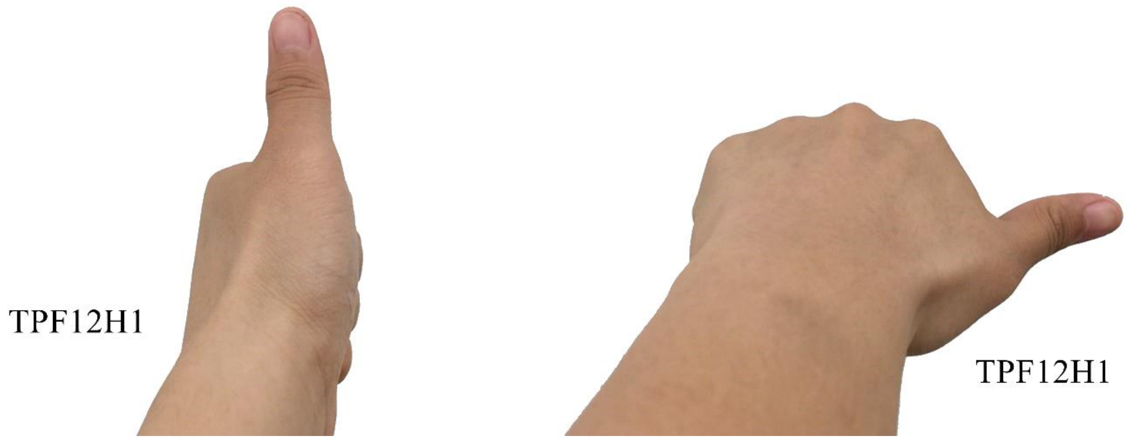


Fig. 4.21 Gesture combination

The combination of all the above gestural components construct the human gesture. (Refer to Figure 4.21). The total number of the supported gestures of the system can be calculated by

$$\mathrm{N} = \mathrm{T} \times \mathrm{F} \times \mathrm{H} \qquad (4-1)$$

where T is the supported touch commands, F is the supported finger formations and H is the supported hand postures. In this case, the result will be hundreds, which is far more than the average typical commands needed for most applications. In a practical application, we just need to select the appropriate gestures. Figure 4.21 presents different hand postures with the same finger formation. Therefore, the meaning is different according to our gesture ID protocol, where T means touch command label, P is the touch ID meaning the palm was activated, F is the finger formation label, 12 is the finger formation ID, H is the hand posture label, and 1 is the hand postures ID.

4.4 Applications

4.4.1 Gaming Control

In order to demonstrate the usability and ease of use of the multimodal data glove, a gaming control application was implemented with the multimodal data glove. With this application, the user is able to use hand gestures to control the game in terms of controlling movement, interacting with other objects in the game and the expression of motions. The structure of this application is shown in Figure 4.22. The data glove system recognizes hand gestures and sends the results to a WinIO virtual mouse and keyboard driver interface. The interface is able to simulate the activities of the keyboard and mouse to interact with the gaming program. World of Warcraft and Diablo III from Blizzard Entertainment were chosen since they have numerous interactive activities and an excellent gaming experience.

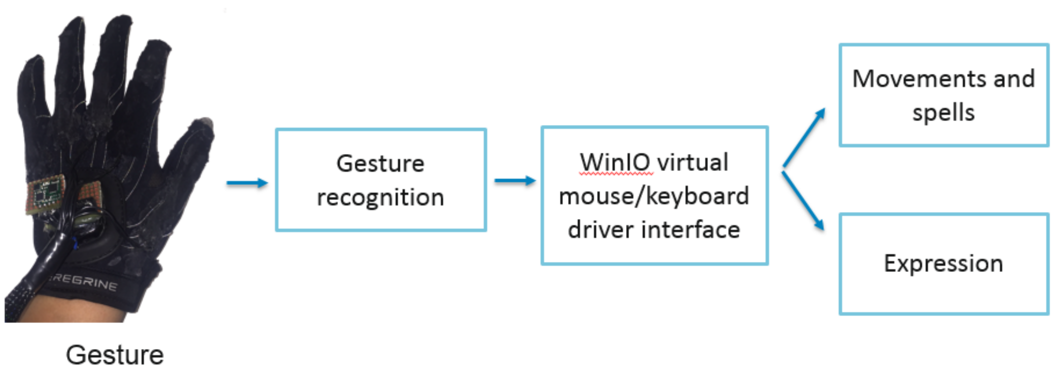


Fig 4.22 Gaming control application structure

Fig. 4.23 Gaming control application

4.4.2 Battle Command Transmission Platform

A potential police command transmission scenario could maximally utilize the properties of our system. Police battle commands are usually a combination of voice commands and gesture commands. However, in some circumstances, voice and radio silence is needed. With the data glove system, those battle command gestures could be recognized by the system and sent to other team members which would help those out of sight from the command sponsor to execute the correct order and execute the proper response. The whole operation can also be seen on a cloud server.

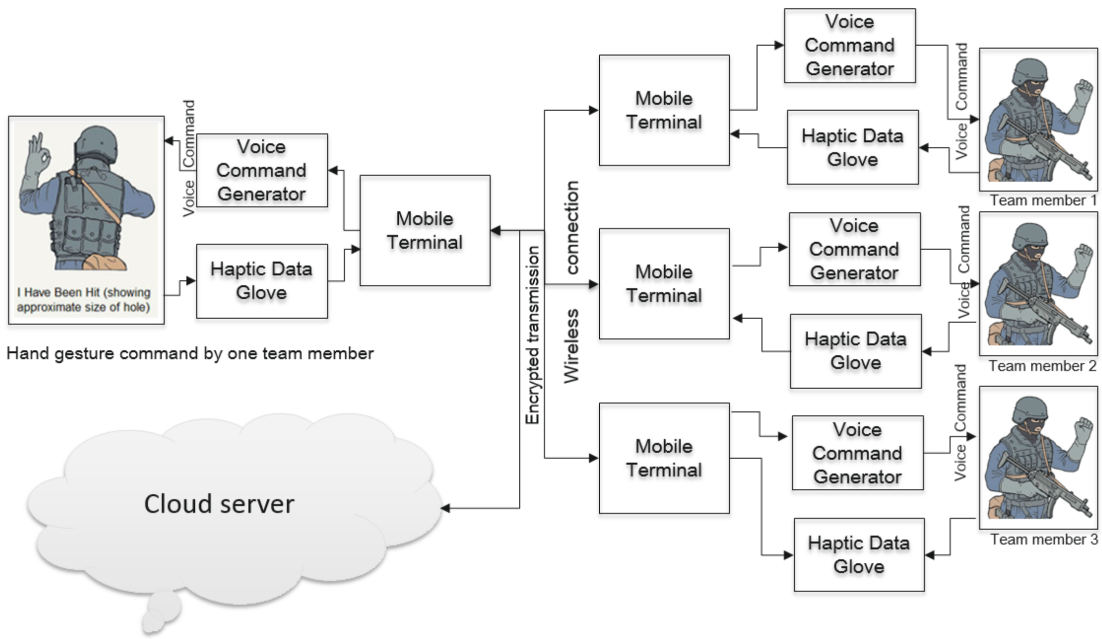


Fig. 4.24 Battle command transmission platform

4.4.3 Map Application Control

In this application, a map application can be controlled by the predefined gestures and touch commands. It provides a natural way for controlling these kinds of applications for computers which have no touch screens. The basic operations with a map application such as navigation (the map will move according to the direction of pointing), zooming in (by flattening all fingers) and zooming out (by making a fist) are supported.

Other applications such as the recognition of referee gestures, dynamic sign language recognition interactions can be done with future development focusing on dynamic recognition approaches. Also, the system can be expanded to smart appliance control, robot control and virtual environment input in the future.

4.5 User Study

In order to test the accuracy and validity of the system, we performed a user study that combined both a subjective user study and an objective user study. A total of 15 subjects participated in the test. 11 Males and 4 Females (Ages 20-30) participated in the evaluation and most of them were graduate students from China and Canada.

4.5.1 Objective evaluation

The objective evaluation measured the objective performance of the data glove system. The test subjects were first taught how to use the glove to perform gestures and to give touch commands. Then a training protocol is followed to build a customized gesture database for the user. We allowed the subject to choose the test gestures themselves for the training process. In the testing phase, we randomly combined the trained gestures into five groups and let the subjects perform each combination gesture five times. We measured the detection precision and failure rate.

The precision is calculated as the ratio of true positive results over all the data detected:

$$\text{Precision} = \frac{True\ Positives}{True\ Positives + False\ Positives} \qquad (4-2)$$

where a true positive is when the result from the test was successful as well as the condition was fulfilled; a false positive was when the condition was not fulfilled but the result was a success.

Also, the touch commands affect the shape of the finger gestures, so the evaluation of the touch commands with hand attitudes was separated from the evaluation of the finger gestures with hand attitudes.

The result of the objective test is shown in Figure 4.25 (a), 4.25 (b) and 4.25 (c).

According to the results, the system provided an average precision of 0.8667 during the objective evaluation. We noticed that some finger formations such as #9 and #15 did not yield satisfactory results since they did not reach 80% of precision. That was because the flex sensor we used here was hard, and it was not easy for some participants to perform some of the gestures that required a full bend in the little finger and ring finger, which lack strength. Also, based on the observation, the inaccurate initial position influenced the precision of the hand posture attitude recognition significantly.

Total Number of Test Attempts	Number of Detection Failures
175	50
Precision	86.67%
Failure Ratio	13.33%

Fig. 4.25(a) Objective Evaluation Results

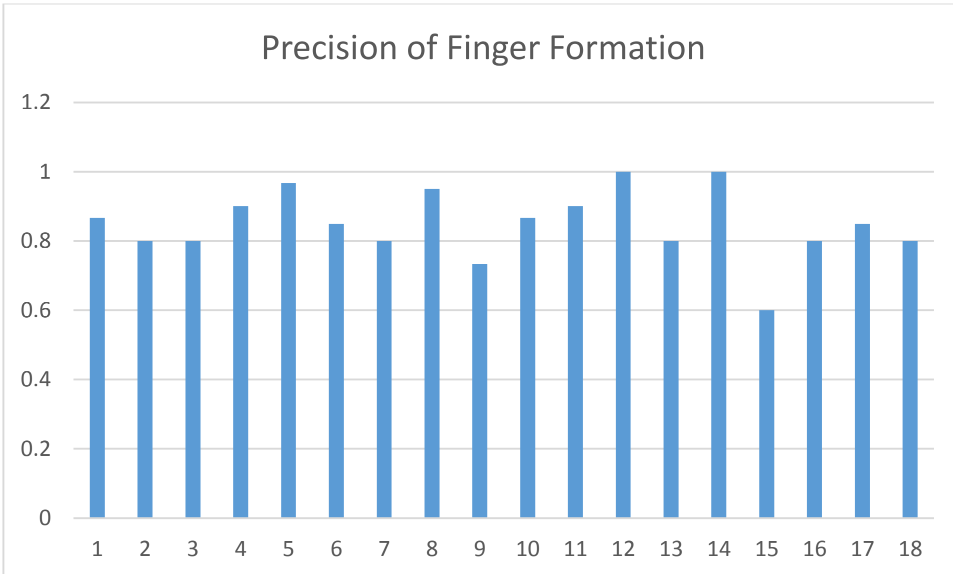


Fig. 4.25 (b) The precision of each of the 18 finger formations from the evaluation

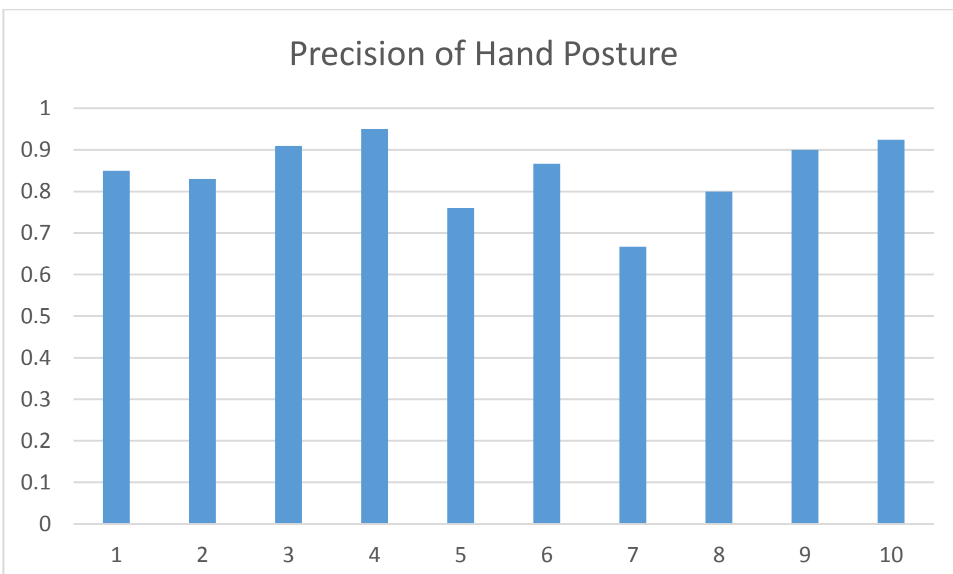


Fig. 4.25 (c) The precision of each of the 10 hand postures from the evaluation

4.5.2 Subjective User Study

The subjective user study aimed to measure the validity of the multimodal data glove. By implementing the gaming control application, the system provided an alternative method of gaming interaction. World of Warcraft and Diablo III were used in this user study. Subjects were first taught how to play the game using the traditional input methods: keyboards and mouse. Then subjects were asked to complete some objectives in the game. Then, subjects were taught how to use the glove system and performed the training process to build the hand gesture database with which they were more familiar. Subjects performed the same tasks that they did by keyboard and mouse. Finally, a questionnaire (See Appendix) was completed by subjects to evaluate their experience during the test. In order to avoid the influence from the keyboard method experience, for those who have played World of Warcraft or Diablo III were asked to evaluate the experience of the game they had not played only. In the end of the subjective user study, two marks of user experience were collected from the participants and we performed a two-tail paired-samples T-test. We expected the user experience of the glove would be better than the keyboard interaction method.

The results are shown in Table 4.3 and Figure 4.26. The results of the first two questions suggests that participants had more of a tendency to believe that they were more in control of the game when using the glove system. Answers to question 3 and 4 suggest that they could trigger the commands correctly both on the glove and the keyboard. Results of question 5 demonstrated that participants thought it was more fun to play games using gestural commands on the glove than the traditional methods. The quality of experience ranged from 0 to 10, 0 representing the lowest quality while 10 representing the highest quality. For the glove, we got an average mark of 7.93, and an average of 6.93 for the keyboard. After preforming a two-tailed paired-sample T-test, we observed a significance of 0.028 which shows that the glove was rated significantly higher on the user experience.

Table 4.3 Subjective user study results

	Totally Agree	**Somewhat Agree**	**Somewhat Disagree**	**Totally Disagree**	**Keyboard**	**Glove**
In control of the game (Glove)	9	6	0	0	N/A	N/A
In control of the game (Keyboard)	9	5	1	0	N/A	N/A
Triggering the correct commands (Glove)	10	5	0	0	N/A	N/A
Triggering the correct commands (Keyboard)	3	9	3	0	N/A	N/A
More Fun	N/A	N/A	N/A	N/A	0	15
Quality of Experience (Glove)	Average of 7.93					
Quality of experience (Keyboard)	Average of 6.93, p=0.028					

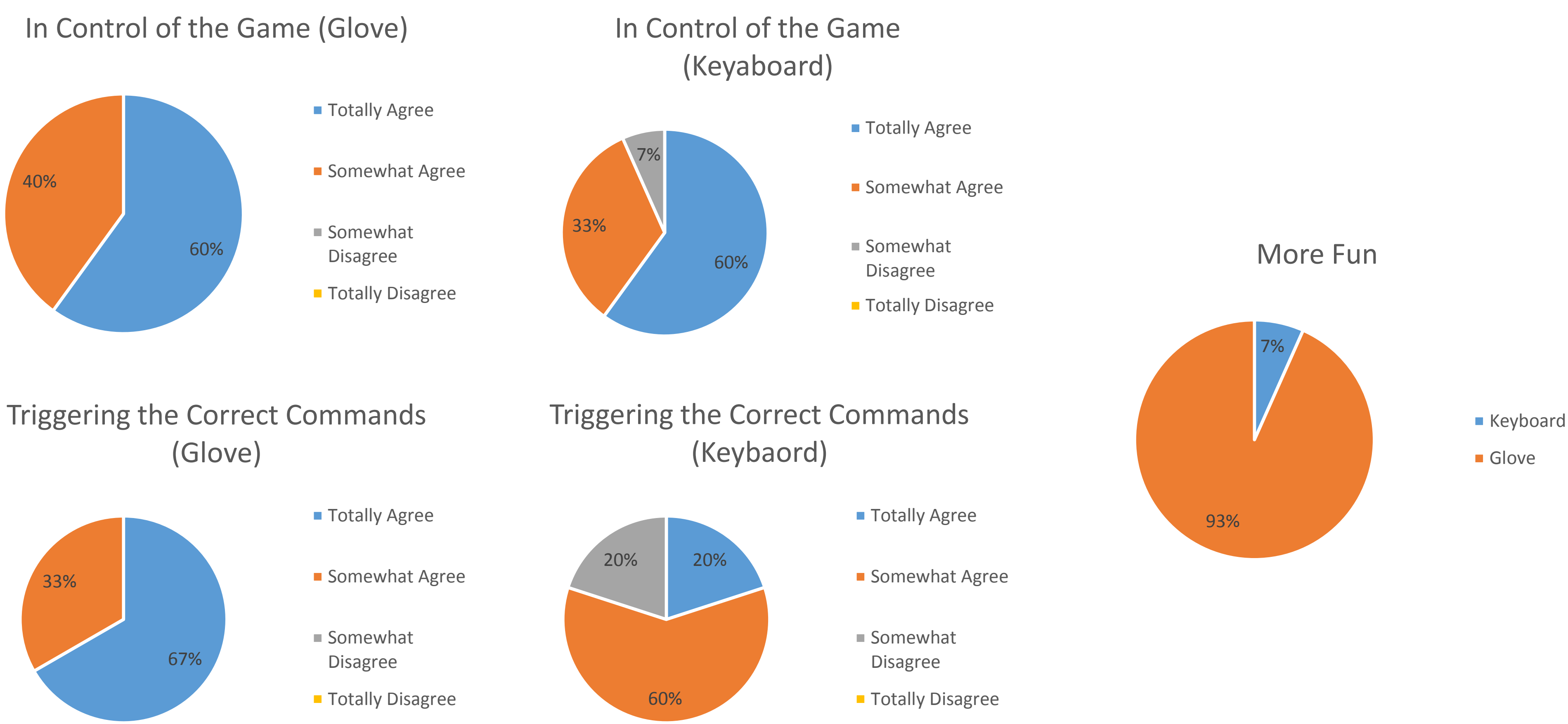


Fig. 4.26 Result of subjective user study

4.6 Summary

This chapter mainly present implementation of the proposed system. In hardware implementation section, we introduced that the choice of the different sensors, and the process of building the circuits. We also introduced the implementation of the hardware level of communication approach for the system. In the software implementation section, we introduced the process of data organizing and transmitting. Liblinear SVM library was used here as the linear SVM training tool. We have shown that the the system supports hundreds of different gestures. In order to measure the validity and ease of use of the multimodal data glove system, an objective user study has been performed to prove the system's high recognition precision (86.67%). Furthermore, a subjective study has been conducted to summarize the subjective experience of a sample of users.

Chapter 5 Conclusion and Future Work

5.1 Conclusion

With the development and expending need of the wearable devices, users are increasingly looking for a natural ways to interact with computing devices such as personal computers, cellphones, tablets etc. In this thesis, we studied the previous research works and products pertaining hand gesture interaction and proposed a new solution in this field: the multimodal data glove system which supports hundreds of gestures, cost very low and very easy to use.

In Chapter 3, we introduced the requirements of the proposed system. We presented the proposed system, from the broad structure to a detailed design. We explained the signal acquisition process, including the resistance rheostat sensor, flex sensor and motion sensor as well as their operating principles, and we also explained two methods:

a lookup table and a Linear Support Vector Machine for recognizing the three kinds of gesture commands. In the end, we summarized the client of the proposed system.

In Chapter 4, by introducing the setup of sensors, the signal acquisition circuit, the communication from sensor to microcontroller and from the microcontroller to upper computer this chapter presents the hardware implementation of the proposed multimodal data glove system. This chapter also introduced implementation of software which refers to the process of data and visualizing the results. Application was also been discussed. And it concluded the validity and accuracy of the proposed system by providing a user study including subjective side and objective side.

5.2 Future Work

Currently, the system can only recognize static gestures, we will continue to work on the recognition of dynamic gestures. And this will expend the potential application into more areas. Also, we now just used one flex sensor on each finger to detect the finger movement. Even though this setup could already provide a significant number of gestures, more sensor can be added between the fingers to measure the relative horizontal movement of fingers. At last, more and more feasible application will be developed to make the system more comprehensive.

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Appendix I User Study Questionnaire

THE MULTIMODAL INTERACTION THROUGH THE DESIGN OF DATA GLOVE USER STUDY

Multimedia Communications Research Laboratory, University of Ottawa, Canada

We highly appreciate your participation and we ensure that the information that you provided in this user study is strictly confidential.

Introduction

This user study you are attending is designed by Bote Han, who is a master student from Multimedia Communication Research Laboratory, University of Ottawa, to evaluate the validity and accuracy of a thesis project: ‘The multimodal interaction through the design of data glove’. The objective of this project is to develop an interaction system based on the actives of hand including both hand gesture and touch commands.

Two sections of test will be performed. Before the test, the participants will have a tutorial to learn how to use the data glove and to have a training process in order to build their own gesture modal.

Objective user study: you will randomly select 5 combination of hand attitude and finger gesture and preform each combination gesture 5 times and the recognition result will be recorded.

Subjective user study: you will be taught to play two computer game: World of Warcraft and Diablo III from Blizzard Entertainment. You will play the two game both by the traditional method: keyboard and mouse and by the data glove to finish a same task. A questionnaire will be provided to evaluate the experience in the subjective user study.

Please provide your signature to confirm that you agree to participate the user study and you understand the introduction above.

Print Name Signature Date

Participant Information

Age: Gender: M/F

Education Background:

Have you ever used a data glove?

Yes□ No□

Have you ever played World of Warcraft or Diablo III?

World of Warcraft Yes□ No□

Diablo III Yes□ No□

Multimodal Data Glove Evaluation #1

Gesture Command Evaluation

Attempted Gesture ID#	1st Attempt	2nd Attempt	3rd Attempt	4th Attempt	5th Attempt

Multimodal Data Glove Evaluation #2

Gamming Application Evaluation

1. **I feel in control of the game when playing using the glove.**

   A. Totally agree **B. Somewhat agree** **C. Somewhat disagree**

   D. Totally disagree

2. **I feel in control of the game when playing using the keyboard.**

   A. Totally agree **B. Somewhat agree** **C. Somewhat disagree**

   D. Totally disagree

3. **I feel that the gestures I make while playing the game using the glove result in triggering the correct commands on the computer.**

   A. Totally agree **B. Somewhat agree** **C. Somewhat disagree**

   D. Totally disagree

4. **I feel that the buttons I press while playing the game using the keyboard result in triggering the correct commands on the computer.**

   A. Totally agree **B. Somewhat agree** **C. Somewhat disagree**

   D. Totally disagree

5. **Which method of controlling the game is more fun?**

   A. Keyboard **B. Glove**

6. **Rate (by circling a number below) your quality of experience when playing the game using the glove (0 refers to the lowest quality while 10 refers to the highest quality of experience).**

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**

7. **Rate (by circling a number below) your quality of experience when playing the game using the keyboard (0 refers to the lowest quality while 10 refers to the highest quality of experience).**

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**

8. **We value your feedback. Do you have any ideas how we might further improve the glove you have just tried?**

This is the end of this user study, we appreciate your participation.