Electromyography-based Mouse Pointer Control

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Abstract

As people become more and more integrated with the personal computers, smartphones, cloud services and various embedded systems, new interfacing options are required to provide faster and more comfortable service than a conventional touchscreen, button or a mouse. One of the possible ways to realize human-machine interface is via electromyographic signals, which are generated by muscles during their contractions and can be analyzed to derive the command to the computer. This technology has applications in prosthetics and rehabilitation as well. The purpose of the project is to implement a Python-based program that allows the user to control the mouse cursor by contracting the muscles of his hand. A software is designed to acquire EMG signals from the Myo EMG armband using Python. The acquired signal is processed by MAV and filtered to obtain a more obvious result, which is directly applied to control the direction and speed of the cursor. As a comparison and improvement of this control method, a classifier based on machine learning algorithm SVM is designed and applied. Through classification, different gestures are identified and corresponded to the direction of mouse movement one by one, so as to realize the uniform movement of the cursor in specific directions. Designed games and experiments, and judged the results of control realization by analyzing the subjects' experience of clearing the game.

Keywords: Electromyography, surface electromyography, multi-channel EMG, cursor control, Myo-armband

1 Introduction

In 1780, the Italian biologist Galvani accidentally discovered the phenomenon of "dead frog movement", that is, when the exposed nerves of the frog's legs were killed with the tip of a

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knife, the dead frog was trembling. He published his exposition on "animal electricity" in the thesis "On the Electricity in Muscles" in 1792. Since then, he has laid the foundation for the study of bioelectricity and proved that muscle contraction is related to electricity.

In 2013, Canadian startup Thalmic Labs launched an innovative armband MYO wristband (gesture control armband). This gesture control armband can be worn above the elbow joint of any arm to detect electrical activity generated by the user's muscles. It wirelessly connects with other electronic products through low-power Bluetooth devices to sense the user's actions. The MYO armband is composed of 8 muscle pulse detection modules, with metal contacts on the inside to detect muscle pulses close to the arm. The Myo bracelet device and wearing method are shown in figure 1.

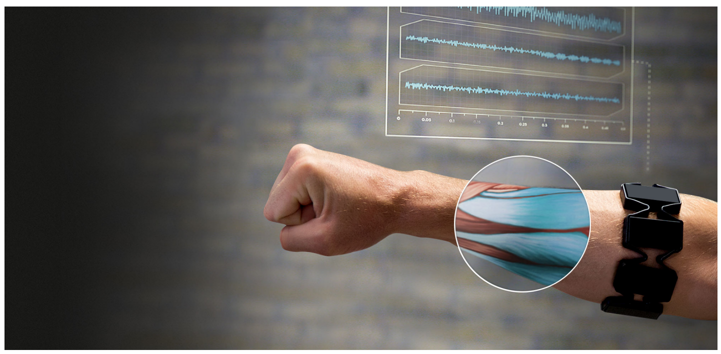


Figure 1: Myo Armband

The characteristic abbreviations of commonly used EMG signals correspond to the following table. Hudgins proposed a feature set, which is composed of mean absolute value (MAV), zero crossing rate (ZC), slope sign change (SSC) and waveform length (WL). This feature set is a feature set in the time domain that can be applied to classification. Englehart tested some time-frequency domain sets (WF, WT and WPT). The experimental results only in the classification show that the time-domain feature set is better than the time-frequency domain set. Jiang uses the root mean square value (MSV) to estimate the force. Fougner evaluated multiple combinations of 15 different EMG functions in order to estimate the joint angle. Research has found that there are differences between each, and using a specific feature set for a specific user will produce the best results.

In recent years with the development of EMG controlled upper limb prosthetic has advanced considerably, due to an increased interest in the area along with higher demands for better prosthetic and more precise control.[1] In the early years most EMG prosthetic functioned by controlling one degree of freedom (DOF) with on-off control, mainly by linking antagonistic muscles to more than one DOF. This kind of prostheses change between states, due to a switching impulse which cause a state machine to shift its present state. Usually a strong and fast muscle contraction is employed to generate the switching signals. This type of control provided users a way to control more than one DOF, but never simultaneously. The switch-control requires the users to go through the movements of the prosthesis to find the one they wanted to perform. As the switching method was slow and

Abbreviation	Name
MAV	Mean absolute value
MSV	Man square value.39
MYOP	Myo-pulse
NT	Number of turns
RMS	Root-mean square
SSC	Slope sign changes
WAMP	Willison amplitude
WF	Windowed Fourier transform
WL	Waveform length
WPT	Wavelet packet tranform
WT	Wavelet transform
ZC	Zero-crossings

Table 1: The characteristic abbreviations of commonly used EMG signals

non-intuitive, more complex methods were introduced to the EMG prosthetic scene. Classification methods effectively enabled users to use DOFs more freely because the switching was now replaced by direct recognition of different muscle contractions linked to specific prosthetic movements. However, classification methods proved to be sensitive to real life conditions, e.g. change in limb position, muscle fatigue and sweating. Introducing regression as a new mapping method in myoelectric prosthetic provided a way to enable both simultaneous and proportional control of multiple DOFs. Regression is able to provide a continuous value for each DOF based on the recorded EMG signal, while a classifier only decides upon a certain class. Which means regression will be suitable to recognize wrist gesture based on 8 channels signals extracted from Myo-armband.

2 Physiological Basis of EMG Signal Generation

The problem of muscles producing bioelectrical signals is, from the forward perspective, how specific mechanisms and phenomena affect the signal, and the reverse problem is how the signal reflects certain mechanisms and phenomena and allows them to be identified and described.

The central nervous system is organized in a hierarchical manner. The exercise program is organized in the pre-exercise cortex, auxiliary motor area and other related areas of the cortex. The anterior motor cortex is located on the outer side of the cerebral hemisphere, and the auxiliary motor cortex is located on the dorsal side of the anterior motor area and extends to the inner side of the hemisphere. The premotor cortex is the primary motor cortex of the frontal lobe of the brain, which is composed of the interconnected areas of the cerebral hemispheres. The cerebellum and, to a certain extent, the input from the basal ganglia (stimulating or inhibiting) neurons of the primary motor cortex, the brainstem and the spinal cord.

Motor Unit (Motor Unit) is the α-motor neuron in the spinal cord (the sum of all descending and reflex inputs) and the muscle fibers it innervates. According to physiological characteristics (such as contraction speed and fatigue (sensitivity to fatigue)), three types of motor units can be identified: (1) rapid twitching and fatigue (type FF or IIb); (2) fast bending , Fatigue resistance (FR or IIa type); (3) Slow twitching (S or I type), the most fatigue resistant.

Analyze the contraction characteristics of different types of muscle fibers from the way to generate ATP for muscle activity and its metabolic byproducts. From the perspective of single fiber action potential and MU action potential characteristics, compared with type I fibers, type II fibers It has more negative resting potential, greater peak excursion, faster rate of depolarization and repolarization, and shortened action potential duration.

The principle diagram of the basic motor unit control mechanism is shown in the figure. The whole process follows this process: the input from the cerebellum, and to some extent the input from the basal ganglia (stimulation or inhibition), to the neurons in the primary motor cortex, Then to the brain stem and spinal cord. Then, the connection between the corticospinal tract and α-motor neurons provides direct cortical control of muscle activity.

In spontaneous muscle contraction, strength is regulated by a combination of motor unit (MU) contraction and activation frequency (rate encoding) changes. The stronger the contraction, the higher the activation frequency, and the greater the strength; 3 It has nothing to do with the type of muscle, gender, age and training status.

Motor units are always recruited in increasing order of α-motor neuron size. There is a positive correlation between the recruitment order of a single MU, peak amplitude and twitch tension, AKA "normal recruitment sequence" or "orderly recruitment". The recruitment and firing frequency (rate coding) of the motor unit mainly depends on the size of the force and the speed of contraction. The number of MU recruited and its average firing frequency determine the electrical activity in the muscle, that is, the same factors determine muscle strength. Therefore, a direct relationship between electromyography (EMG) and applied force can be expected.[2]

3 EMG Signal Processing

3.1 Data Aquisition

EMG signals were acquired by the Myo armband from LS2N which was an 8 channel dry electrode armband with 200 Hz EMG sampling rate and 50 Hz IMU sampling rate. The recorded EMG data was filtered using a 2nd order Butterworth high-pass filter with a 10 Hz cut-off to remove movement artefacts. Only accelerometer data from the IMU was acquired for data processing. The Myo armband has been suggested as a suitable data acquisition system for pattern classification, but not yet for a regression-based control scheme. The armband was placed around the thickest part of the dominant forearm, approximately 1/4 of the length of the forearm distal of the elbow. For a close contact between the forearm and armband, clips were used to tighten the fit if necessary. All data acquisition, processing, data analysis and testing was performed in Python. [] But the electromyographic signals (EMG) from Myo-armband sensors were going to be used to conclude signal processing techniques following. A buffer in a constant size was set to store the acquired data in deque format.

3.2 MAV Calculation

3.2.1 Mean Absolute Value

The sEMG signal is essentially a weak electrical signal, which is extremely susceptible to noise caused by environmental noise, power frequency interference, and physiological factors. Its signal-to-noise ratio is low, and there are more glitches in the signal. In order to obtain a smoother signal and to better realize real-time performance, the experiment in this paper uses a simple preprocessing method. Since the energy generated by the target action muscle is small, in order to make the amplitude of the activity segment more obvious, the mean absolute value (MAV) processing method is adopted for the collected signal.

For any segment of surface EMG signal, the absolute average value of the signal is the traditional method to detect the level of muscle contraction. The MAV function can estimate the average energy of the signal x in a window containing N samples. It can be expressed as:

$$MAV = \frac{1}{N}\sum_{k=1}^{N}|x_k|$$

Among them, x is the kth sample in the window.[3]

After MAV processing the original data, the resulting graph is as shown in the figure below:

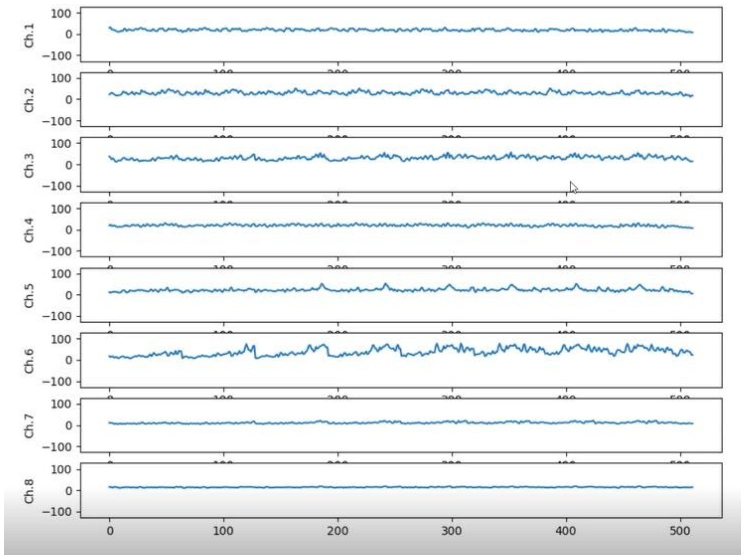


Figure 2: MAV result

It is easy to see that the EMG signal after preliminary MAV processing is not smooth enough to achieve the expected result, and there is also a problem of periodicity. In order to reduce the interference caused by environmental factors, consider applying filters to process the signal.

3.2.2 First-order IIR Filter

Comparing the two digital filters IIR and FIR, according to the difference of impulse response, the digital filter is divided into finite impulse response (FIR) filter and infinite impulse response (IIR) filter. For FIR filters, the impulse response decays to zero in a finite time, and its output depends only on the current and past input signal values. For the IIR filter, the impulse response should theoretically last indefinitely, and its output depends not only on the current and past input signal values, but also on the past signal output values.[4]

FIR is a finite impulse response filter. Limited means its impulse response is limited. Compared with IIR, it has the advantages of linear phase and easy design. On the other hand, to design a filter with the same parameters, FIR requires more parameters than IIR. This also shows that the amount of calculation of DSP should be increased. DSP needs more calculation time, which has an impact on the real-time performance of DSP. In terms of performance, the IIR filter transfer function includes two sets of adjustable factors of zero and pole, and the only restriction on the pole is in the unit circle. Therefore, a lower order can be used to obtain high selectivity, a small storage unit is used, a small amount of calculation, and high efficiency; the pole of the FIR filter transfer function is fixed at the origin and cannot be moved. Change its performance. Therefore, to achieve high selectivity, a higher order must be used. In summary, IIR is selected. The calculation equation for N-order IIR is:

$$y_n = \sum_{i=0}^{N} b_i x_{n-i} + \sum_{i=1}^{N} a_i y_{n-i}$$

Considering that this project intends to complete the task of using the EMG signal to control the cursor movement and does not require a very high order filter, first test whether the first order IIR filter can meet the requirements.

The first-order IIR filter formula is as follows, and the schematic diagram is shown in figure 3.

$$y_n = b_0 x_n + a_1 y_{n-1}$$

Among which, $b_0 = 1 - a_1$, $0 < a_1 < 1$. The smaller the filter coefficient, the smoother the filter effect, but the lower the sensitivity; the larger the filter coefficient, the higher the sensitivity, but the more unstable the filter result.

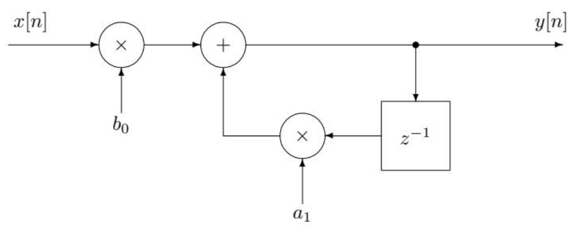


Figure 3: First-order IIR filter

The iteration in the implementation of the IIR filter completes the role of the MAV. Change the size of parameter a to find a suitable value. Finally, we get a=24/25 to filter and process the EMG signal. Because iterative calculation is applied in filtering, the first-order IIR filter is directly used to replace the role of MAV. The waveform after applying the filter is shown in figure 4:

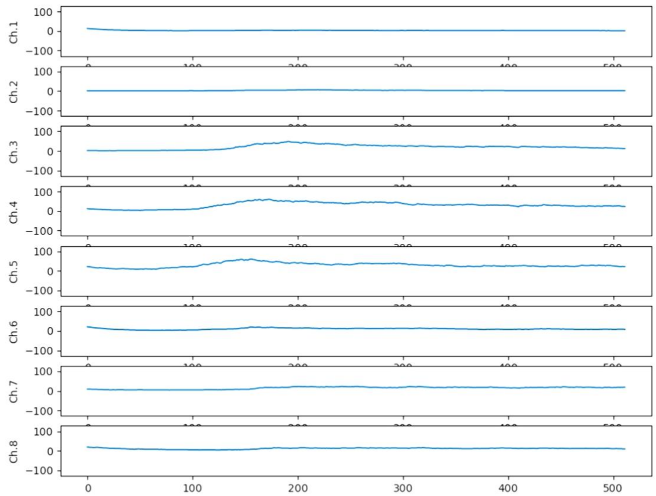


Figure 4: MAV after first-order IIR filter

It can be seen that irrelevant waveform interference is filtered out, leaving the waveform smooth and easy to identify. The frequency spectrum analysis of the waveform before and after filtering is shown in figure 5. The filtering effect is sufficient, and there is no need to use a higher order filter.

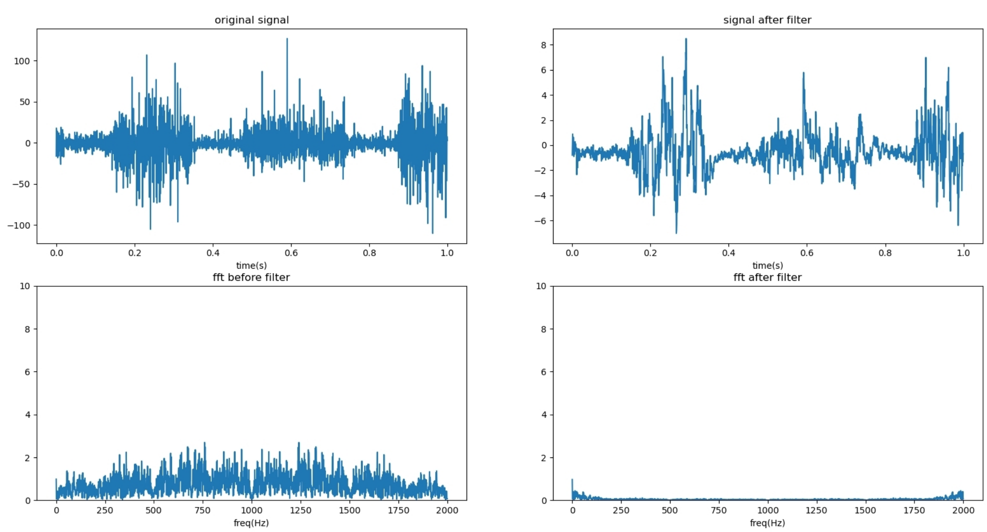
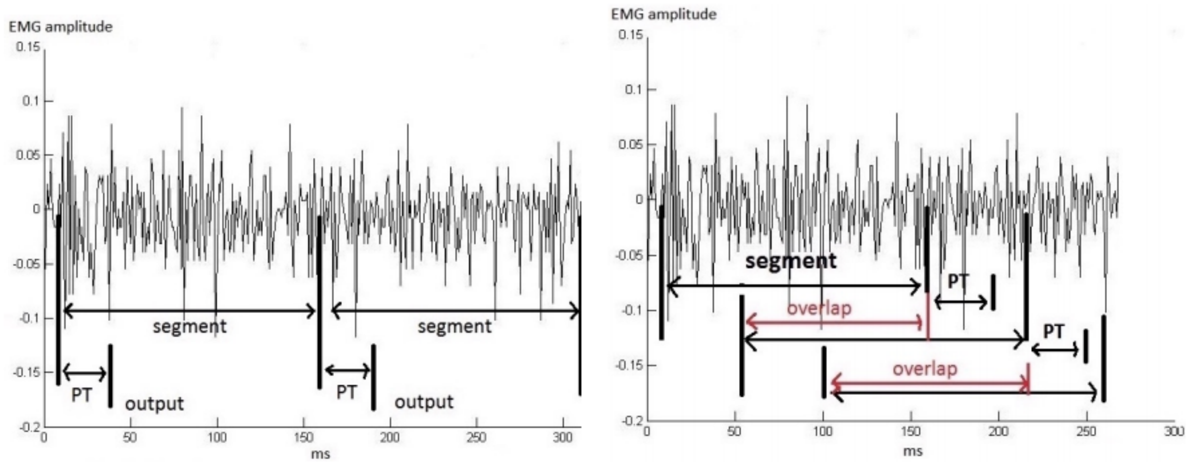


Figure 5: Spectrum analysis after first-order IIR filter

3.3 Windows Overlap

Apply overlapping windows to the signal. Overlap allows more classifications to be generated during the selected processing delay, thereby increasing the stability and accuracy of the control. The principle of overlapping windows is shown in figure 6.[5]



(a) Signal windowing without overlapping

(b) Signal windowing with overlapping.

Figure 6: Windowing Overlap[6]

3.4 Classification

In a previous study [7], they did a comprehensive comparison between some state-of-art classification techniques. The conclussion of their work is kernel ridge regression (KRR) outperformed the other methods. However, the Linear Regression methods are still fist choices for simple data-set because of the lower computational cost compared with KRR.

Considering that the data set of this experiment is collected from subjects in real time and involves the processing of non-linear samples and small samples, Support Vector Machine (SVM) is used as the implementation algorithm.[8] SVM is a classic and applicable small-sample learning method with a solid theoretical foundation. It basically does not involve probability measurement and the law of large numbers, and it also simplifies the usual classification and regression problems. The final decision function of SVM is determined by only a small number of support vectors, and the complexity of the calculation depends on the number of support vectors, not the dimensionality of the sample space, which avoids the "dimension disaster" in a sense. A small number of support vectors determine the final result, which can not only help us grasp key samples and eliminate a large number of redundant samples, but also destined that the method is not only simple in algorithm, but also has better robustness.

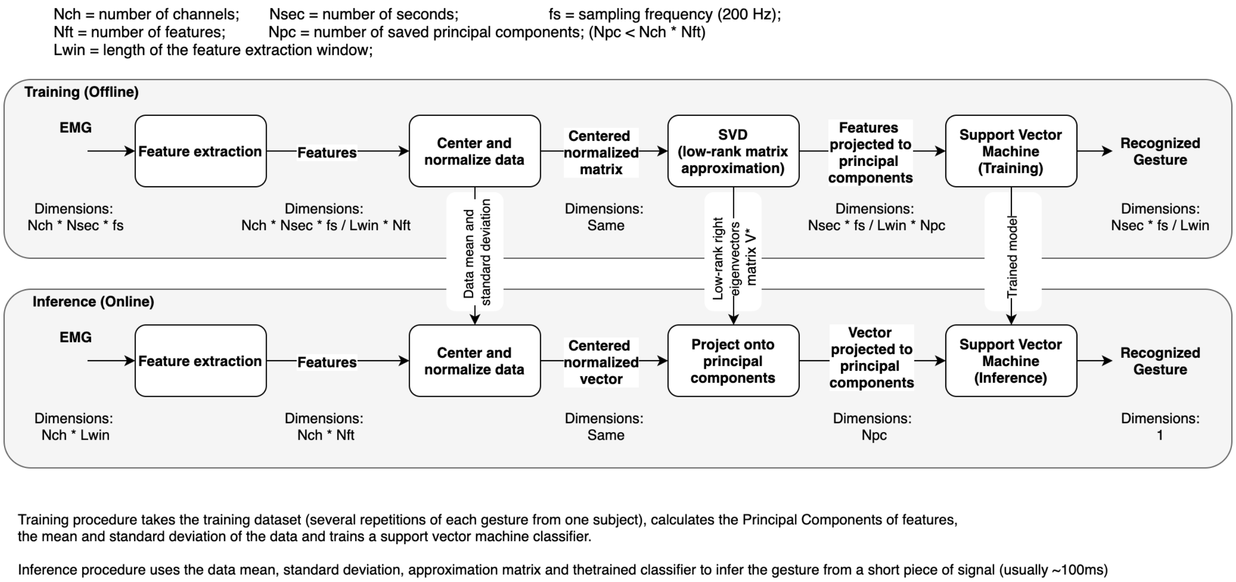


Figure 7: Gesture Recognition Workflow[9]

The process of using SVM for gesture classification follows the following process, as shown in the figure 11. Collect the original EMG signal through the Myo bracelet, and perform feature extraction on it. The extracted features are normalized to obtain a centered normalized matrix, which is then subjected to Singular Value Decomposition (SVD) for dimensionality reduction. Then apply the SVM algorithm for training, and get classified gestures. The offline training is completed, and then online inference will be conduct. The online inference follows a similar process. The signal features are normalized to obtain a centered normalized vector, which is projected to the principal component and then apply SVM for inference.

4 Cursor Control

Cursor control is a highly practical application of electroencephalography(EEG) signals even EEG-based Brain-computer Interfaces(BCIs). An EEG-based BCIs cursor control was proposed as early as 1991.[10] In our project, a cursor control objective was required not only for testing signals but also am important application. To evaluate the control properties and performances, we also designed two small games to test.

4.1 Pyautogui

PyAutoGUI lets your Python scripts control the mouse and keyboard to automate interactions with other applications. The API is designed to be as simple. PyAutoGUI works

on Windows, macOS, and Linux, and runs on Python 2 and 3.
PyAutoGUI has several features:

Moving the mouse and clicking or typing in the windows of other applications. Sending keystrokes to applications (for example, to fill out forms). Take screenshots, and given an image (for example, of a button or checkbox), find it on the screen.

Locate an application's window, and move, resize, maximize, minimize, or close it (Windows-only, currently) Display message boxes for user interaction while your GUI automation script runs.[11] The function of controlling cursor movement and keyboards

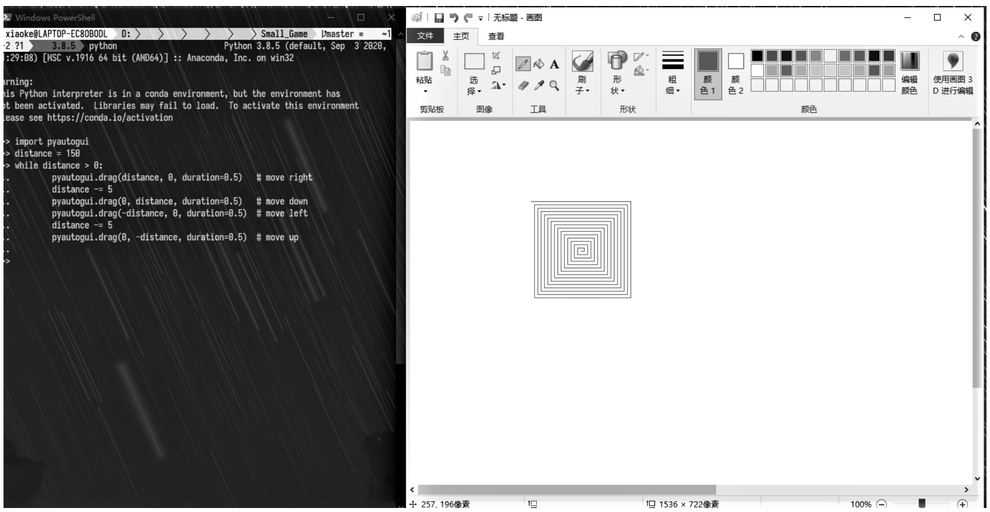


Figure 8: Example of using pyautogui to control cursor

pressing were used to our project and following games.The Fig.8 shows a example using pyautogui to control cursor whose track was shown on a drawing board.

4.2 Gesture Selection

The wrist is a complex series of joints that are formed around the carpal bones and the radius and ulna (forearm bones). The wrist is capable of three sets of distinct movements Flexion and extension, Supination and pronation, Ulnar deviation (ulnar flexion) and radial deviation (radial flexion). From these 3 pairs we empirically selected two distinct pairs ulnar(radial) and extension(flexion). [12]

4.3 Cursor Control without Classification

The first system was controlled by MAV signals after IIR filter directly without any classification models. After observing MAV streaming signals responded by four gestures mentioned before and find the differences and select particular channels to control each movement of 4 channels.

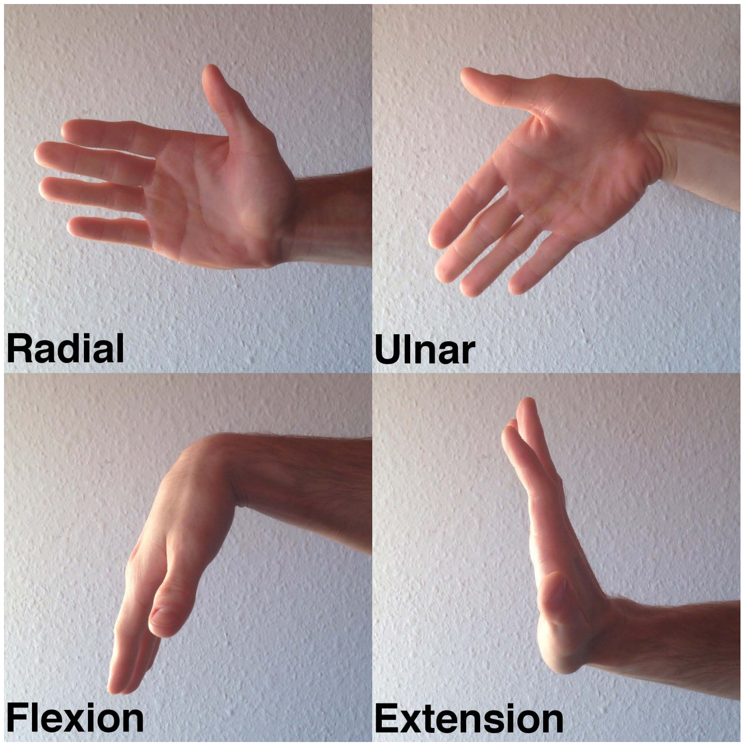


Figure 9: Four used gestures to control cursor

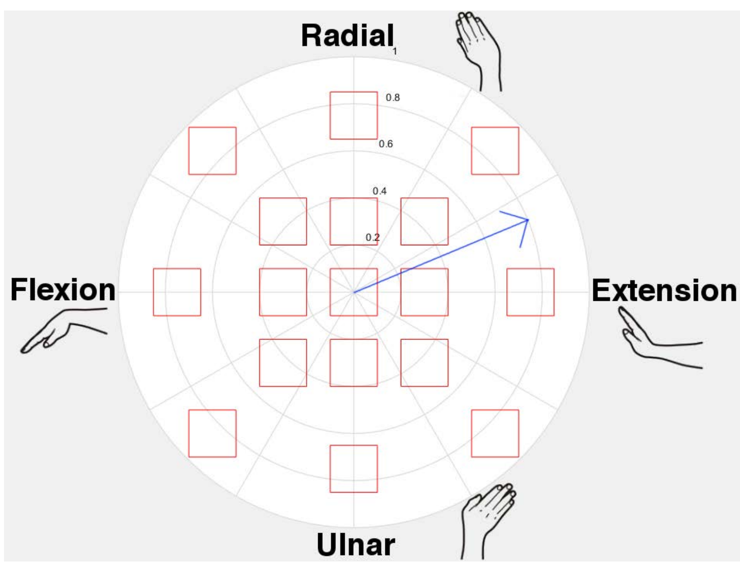


Figure 10: A vector originating from origin depicted vector coordinates based on MAV signals.[13]

Eventually, the cursor couldn't move left. Because in the collected signals, the channel activation caused by the gesture of moving left is particularly confusing. More than half of the channels have generated activities that exceed the threshold, but no one suitable for characterizing the left-hand movement can be found. Also, the cursor will shake, which means cross-talk between four selected channels will make a decreasing effect for cursor control.

4.4 Cursor Control with Classification

Because of running out of time for this project, we select this classifier to train under Dr. Konstantin's suggestion which was based on his work.[14] In this classifier, support vector machine (SVM) was applied.

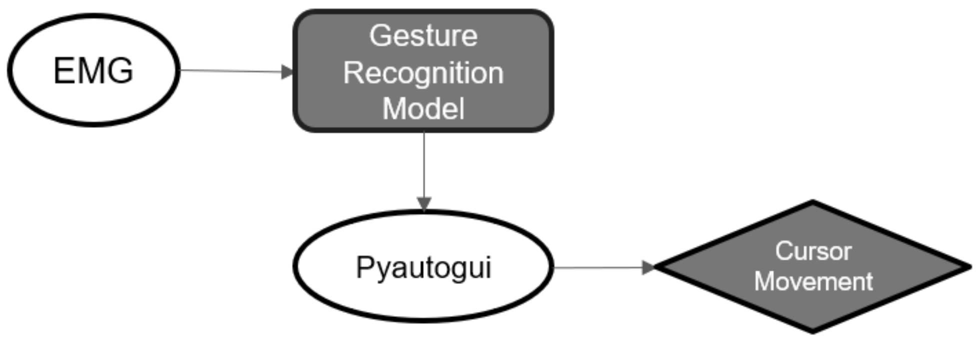


Figure 11: Flowchart of cursor control with classification

Applied this SVM classification model in the flowchart as shown in Fig.11. Fist step should define the target gestures and run for getting data matrixes for further model machine learning. Four gestures should be posed during sampling to make sure the input of learning correctly. Based on results, we need to set a proper trials. When the model complexity is too large for a given dataset. Empirically we set the trails of sampling 3 which suppose to get a appropriate model. Also from robustness evaluation of regression based on myoelectric control against arm position change and donning/doffing. [15] Changes in arm positions significantly influence the offline performance. So not only trials in offline sampling will affect result, but also robustness is also important.

5 Game Design

5.1 Maze Game

To design a game that can be used to evaluate the sensitivity and accuracy of EMG-baesed cursor control, consider a pointer-controlled game. The basic rule of this game is to lead the blue dot representing the player from the entry to the exit of the the randomly generated maze through the movement and click of the cursor, which should be controlled by the

EMG signals. The blue dot can move one step at a time into adjacent squares. The game will be timed, and the timing result will be used to determine the player's performance in the game, which can reflect its control of the EMG-based mouse.

The figure 12 below is the screenshot at the beginning and end of the game.

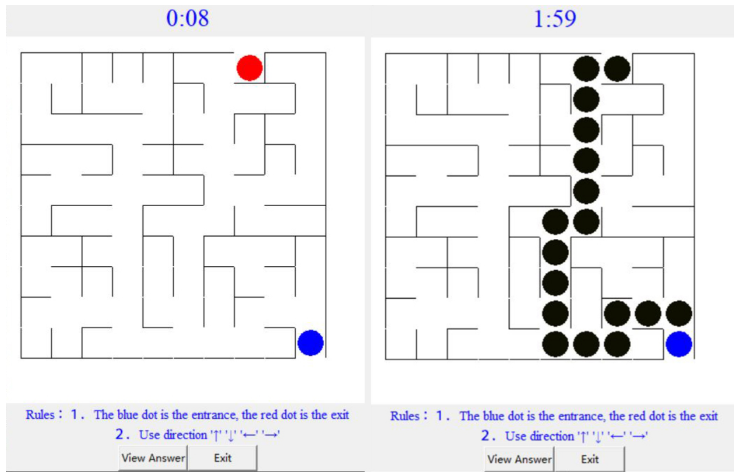


Figure 12: Maze Game

5.2 Shooting Game

Except maze game introduced above, we still designed the other small game to evaluate the controlling performance.This game is also based on pygame[16] frame and is not controlled by keyboard rather than cursor. The four gestures get from the classification model will used to control the movement of our character to escape enemy's attack and lead off attack. Also the gesture "fist" was used to shoot bullets.

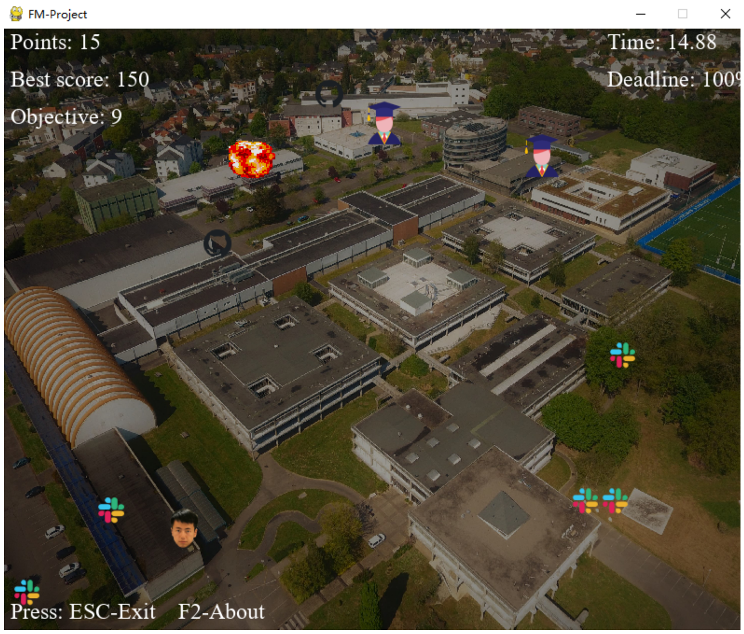


Figure 13: Shooting game

Use Armband to control character's movement and maybe also the other gesture except 4 direction control channels to control shooting. The character should move to escape the enemy's shooting and defeat enough enemies to win the game. The enemy's bullet is the logo of "slack" which reflects our supervisor's messages which can push use to work. The character's bullet is the logo of "github".

5.3 Experiment and Analysis

5.3.1 Experiment Design

In order to test the sensitivity and accuracy of the cursor controlled by EMG, an experiment is designed and subjects are invited to participate. Invite the subjects to participate in a small game. This game should have been the airplane war or maze game mentioned above, but in order to simplify the experiment process, we apply a simpler game interface here. The red area in the lower left corner of the computer screen is the departure area, and the blue area in the upper right corner is the arrival area as shown below.

Subject	Time (s)		
	1	2	3
Subject 1	63.51	59.17	82.32
Subject 2	45.39	48.31	53.35
Subject 3	49.87	42.35	64.93

Table 2: Results of Experiment

Figure 14: Test Interface

The subject wears the myo band and controls the cursor movement through gestures. The movement of the cursor from the departure area to the arrival area is regarded as a whole process.

Each subject first follows the instructions and collected their own EMG signals of different gestures as a training set. After a rapid classification process, the subject starts the game. The first game is played directly after the collection of the training set, without removing the band. After recording the game duration of the first game, immediately play the second game and record the duration of this game. Then the subject takes off the armband and puts it on again in the same position. Record the duration of the third game.

The subjects participating in the experiment were one man and two women, both aged between 20 and 25 years old, in good health and without disabilities. They all use the right hand, which is their dominant hand for experimentation.

5.3.2 Results and Discussion

After experiments, the data is as follows. Observing the data, it can be found that when the subject takes off and puts on the armband, the game result is significantly worse. This is because the EMG signal is collected by the 8 channels of the myo band. These 8 channels are evenly distributed in a circle of the forearm muscles. The data set used for SVM classification is obtained from the first acquisition, and there will be a slight displacement after re-wearing. Any slight displacement, whether horizontal or vertical, may cause inaccuracies. In order to solve this problem, measures can be taken to enrich the training set. The original collection method is to keep the position of the bracelet unchanged. Now we can try to move the position of the armband slightly, and then collect a few more sets of data for classification.

We had expected the subjects' skill level to increase, but unfortunately not all subjects performed better in the second game than the first. This may be because for this extremely simple game, the result of machine learning has a far greater impact on the completion time than the subject's own experience. It may also be because the sample size is insufficient, so that we can not make accurate judgments.

We found that there is a big difference in levels between subjects, which might be caused by the relatively small training set samples. Because of the small number of samples, even if an algorithmic support vector machine suitable for small training sets is applied, slight fluctuations in the signals collected by the subject will have a great impact on the results, which may lead to differences in the completion of the game between individuals.

6 Conclusion and Future Work

The purpose of this paper is to find a more convenient way of cursor control by studying the EMG signal.

Throughout the study, we use the Myo armband to collect real-time EMG signals, which can be initially used for mouse control after average absolute value and filtering. Connect the 8 channels that represent the muscles of different parts of the arm with different directions. For each gesture, there are 2 to 4 channels that can most clearly characterize its characteristics, which can be combined with package pyautogui to achieve mouse control. But this method has obvious disadvantages. Each direction is represented by a single channel, and the channels activated by different actions may overlap, which causes confusion in mouse movement. Therefore, in order to better recognize gestures, we apply machine learning to classify gestures.

Support Vector Machine has the characteristics of low risk, and when the number of samples is small, it still has a higher accuracy rate than other classifiers. Considering that the equipment has a low collection frequency and we do not have a large enough data set, so this classifier is used. The gestures classified by SVM are associated with mouse actions, and the results obtained are significantly better than those without classification. In conclusion, conventional EMG signal processing methods is less helpful for further control tasks than classification models based on machine leaning.

As for future work, it can be considered from two aspects: algorithm optimization and experimental verification.

In this experiment, SVM did not quote enough eigenvalues. In order to make the classification result better, the features in the support vector can be enriched, such as Zero-Crossing (ZC), Waveform Length (WL), etc. At the same time, considering that the EMG signal of the same movement changes with the change of the limb position, which reduces the accuracy of control, we can try to use the linear regression method as a model. The linear regression method is a novel control method that has been proven to be robust and proportional control. The linear regression model can be used as a control group and compared with the completed classification to test the performance of the effects of changes in limb position in different models. As for the classification, we can also consider fusion with other algorithms, such as adding a Convolutional Neural Network (CNN) before SVM to make the algorithm more powerful. For example, combining the advantages of a convolutional neural network with the stability of a support vector machine, using the trained convolutional layer and pooling layer to extract the features of the picture, putting it into the support vector machine for training, and performing classification operations.

For the experimental design of the cursor control effect, the number of subjects and experiments can be increased, and the difficulty of the game can be increased at the same time. In the existing experiment, a quite simple test was conducted , in which it is difficult to see whether the level of control of the subjects increases with experience. The limited number of subjects and the number of experiments also limited the analysis of results. The sample data can be enlarged to obtain more reliable conclusions.

7 Acknowledgment

The authors would like to thank Centrale Nantes for providing equipment. Additionally an acknowledgment to the game test volunteers for participating. In this difficult time, all the expressions and emotions were hidden under the mask, but my dear classmates and professors of ECN helped us through the difficulties.

Thanks to our supervisor Dr. Konstantin Akhmadeev for his patience in giving us professional advice even though our academic level is not high and always ask some stupid questions, even our question and academic performance seem not professional. His wisdom and gentleness are the driving force for us to move forward.

Thanks my partner Xiaoke (Tianyu). We have encountered many problems. As green-hands of EMGs and python, and we were struggling but leaned from errors, grown from failures.

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