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A Wearable and Portable Real-Time Control Gesture Recognition System for Bionic Manipulator

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Abstract. The dexterity and coordinated movement of the hand play a very important role in people's daily life and interpersonal communication. For patients with hand amputation, there are many inconveniences in life. However, prosthetic limb can help them to carry out daily life in accordance with their own intention to meet the basic grasp and interpersonal gesture needs of daily life, which can greatly improve the quality of life of patients. The bionic manipulator is such a humanoid prosthetic limb for the rehabilitation of amputees and is controlled by the surface electromyography (sEMG) signals on the surface of the human body. In this paper, a wearable and portable gesture recognition system based on pattern recognition algorithm is established to control the bionic manipulator in real time. We enhanced the accuracy in each step of signal acquisition and processing. By analyzing the mechanism and characteristics of sEMG signals, we determined the gestures to be identified, the areas of muscle, the number of electrodes, and the placement positions. Our self-developed acquisition device was used to acquire 4-channel forearm sEMG signals and data preprocessing, window sliding, feature extraction, gesture classification were conducted.

1. Introduction

The dexterity and coordinated movements of the hands play a very important role in people's daily life and interpersonal communication. However, due to natural disasters, accidents, and congenital diseases, some people's limbs have different degrees of disability. There is no deny that physically disabled people have huge burdens on society and at home, and also hurt mentally. Prosthesis is one of the important means to enable people with disabilities to carry out their daily lives. For patients with amputated hands, the robot can be controlled according to their own intentions, which can meet the basic grasping and interpersonal gesture needs of daily life.

At present, the common commercial robots are mainly divided into decorative robots, cable-controlled robots and EMG robots. The decorative manipulator only helps the patient to restore the natural appearance and body balance from the appearance, and cannot realize the manual movement function. The cable-controlled manipulator is mainly controlled by the patient by pulling the rope through the stump, which does not meet the normal human nerve control pathway. The EMG

manipulator is controlled by bioelectric signals generated when the human muscles autonomously contract. It has a variety of controllable modes and can achieve basic hand gestures closer to the human hand. Surface electromyography (sEMG) is an electrical signal generated by muscle contraction during limb movement and is an important method for noninvasively detecting muscle activity on the body surface [1]. Compared with implanted muscle electrical signals, sEMG has been widely used in the field of rehabilitation because it does not cause surgical trauma and is closely related to muscle movement. Some patients lost their arms but their nervous system did not damage. Through phantom limb imagination, the information contained in the sEMG signals was taken advantage of to accurately identify the intention of the brain. Patients with congenital disabilities can also generate corresponding EMG signals through training, thereby control prosthetic motion.

Nowadays, some companies and research institutes have done a lot of research on multifunctional human-type EMG prosthetic limbs, which make the robots functionally close to human hands. In order to realize action recognition accurately, feature extraction and pattern recognition are the keys of the whole system. Some commonly used feature extraction methods are as follows: time domain analysis, frequency domain analysis, parameter model and time-frequency domain analysis. Experiments show that the frequency of EMG signals is usually between 0 and 500Hz, and the maximum frequency of power spectrum varies with muscle, usually between 30 and 300Hz. Phinyomrk et al. [2] extracted mean frequency and peak frequency to recognize gestures and found that the classification of features in frequency domain is slightly better than that in time domain. Wavelet transform is a new time-frequency analysis approach, which can capture the local characteristics of the signal. Hu et al. [3] extracted the features based on wavelet transform and wavelet packet transform to improve the classification and recognition rate of surface EMG signals. The methods currently used for EMG control include threshold-based decision-making, threshold-based coding, hierarchical control decision-making, and pattern recognition [4], while pattern-recognition-based EMG control has many advantages, such as conforming to human brain will control. It has been widely used in the control of prosthetic limbs. Recently, the methods of pattern classification for sEMG signal mainly include maximum likelihood classifier, clustering method, neural network and support vector machine (SVM). Chen et al. [5] utilized deep neural network to classify six types of hand movements, and the resolution accuracy reached 96.2%. Singh Rckhi et al. [6] extracted the characteristics of six kinds of motor EMG signals of the hand and then used SVM to classify them, achieving more than 90% classification effect.

Many commercial manipulators use EMG signals to control prosthetic limbs, allowing patients to control the manipulator with their own intentions. However, its high cost and complicated configuration make it difficult for most patients to receive. Although the current research on the application of sEMG signals and manipulators has made some progress, there are still many problems that need to be solved, such as the low quality of acquired raw signals, unstable overall recognition rate of gestures, and limited recognizable actions. Besides, the software training platform currently does not have a complete set of acquisition equipment. Without a complete acquisition-training flow, the bionic manipulator is not easy to be popularized in the disabled population. Therefore, the research is based on surface muscles. Bionic manipulator control of electrical signals is of great significance.

To address these problems, this paper designs a hardware-based gesture recognition system that controls the communication, sampling rate, acquisition mode and other related parameters. It can accurately and effectively receive uploaded data and draw real-time waveform. It can perform feature extraction, classification, feature storage and network training. It integrates functions of data active segment detection, serial port communication, etc., realizing real-time control of the manipulator.

2. Acquisition device design

2.1. System Architecture
The overall flow of the entire system is: First, the electrodes were attached to the forearm of the subjects to acquire the sEMG signals. Next, the sEMG signals were amplified by the built-in PGA amplifier in the hardware device, and transmitted to the host computer through wireless networking. Then, the raw

signals were preprocessed to remove power frequency interference, high frequency noise and baseline wander by Matlab in the host computer. After preprocessing, features were extracted and sent into classifier for gesture recognition. Finally, the control instructions corresponding to the gesture labels were output to control of the bionic manipulator in real time. Figure. 1 illustrates the schematic diagram of the wearable and portable real-time control gesture recognition system.
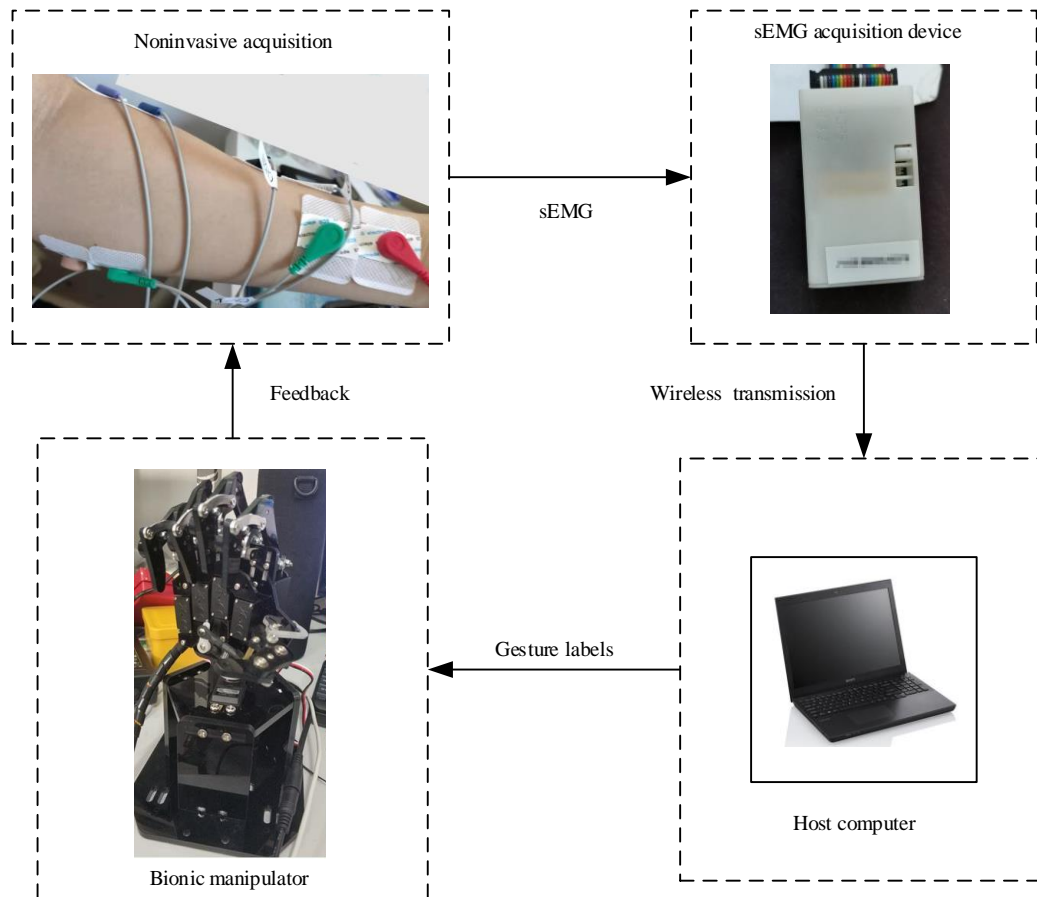

Figure 1. Schematic diagram of the proposed real-time control gesture recognition.

2.2. Signal acquisition position
We apply snap-in electrodes, in conjunction with self-designed acquisition electrode lines and acquisition devices to obtain sEMG signal data. Placing the electrodes on a suitable muscle position can acquire the electrical signals of the muscle related to the hand gesture, and can also simulate the control circuit of the muscle and nerve of the normal human body, so that the users feel the installed bionic manipulator integrates with their own forearms, making the EMG control more intuitive. According to the corresponding relationship between the relevant muscle position and the gesture, the recognition of finger movements needs to collect the EMG signals of the extensor hallucis longus, extensor digitus and long palm.

2.3. Acquisition hardware circuit
The circuit design is based on the ADS1299 high-precision Analog-to-Digital Converter (ADC), which meets the needs of multi-channel EMG signal acquisition and is equipped with a lithium battery. The signal input port uses a standard 20pin-JTAG port, which improves compatibility and versatility. The board is also equipped with a Micro-SD card slot, which can store the collected data in the SD card for later or offline analysis. Figure. 2 shows the hardware structure diagram.
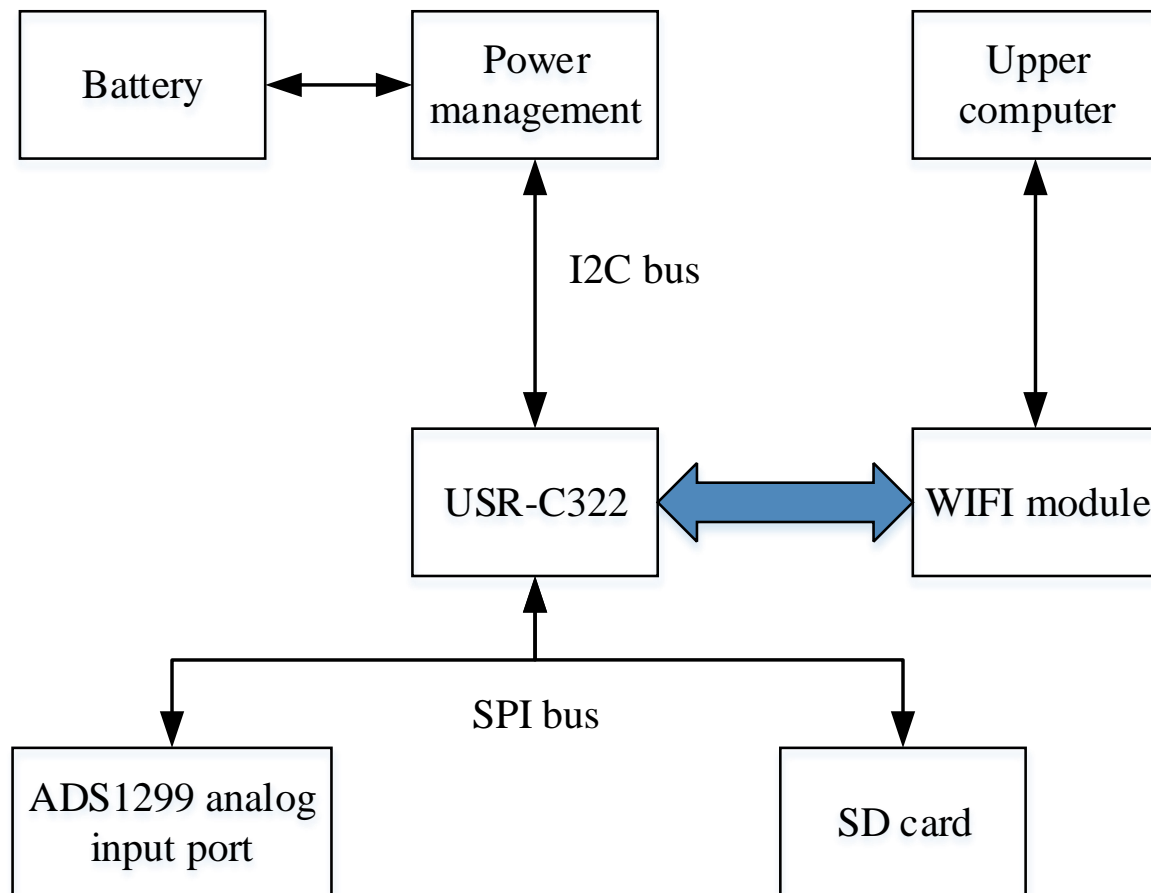
Figure 2. The hardware structure diagram.

The hardware circuit relies on the control of the USR-C322 chip to make each functional part work in sequence. It communicates with the ADS1299 and SD card through SPI to transmit and collect data; it communicates with the battery monitoring chip LTC2942 through the I2C bus; and the entire circuit is built in the USR-C322. The WIFI module communicates with the host computer.

2.3.1. Power management. A 430mAh/3.7V Li-ion battery is equipped, it has the advantages of low internal resistance, high capacity, rapid charge and discharge, low self-discharge, high stability, etc. It has been verified through experiments that it can work continuously for 13 hours at maximum power, up to 24 hours in normal mode. The hardware circuit is divided into shutdown (charging) mode, normal mode and debugging mode. The micro-USB port is used as the charging and program debugging port of the circuit board to charge the Li-ion battery and download programs to the USR-C322. At the same time, in order to collect clean, high-quality EMG signals, a symmetrical design of positive and negative power supply is adopted. This power design not only improves the stability of the ADC and the accuracy of the reference voltage, but also simplifies the difficulty of electrostatic shielding protection design.

2.3.2. Acquisition chip. Considering the universality and compatibility, a 20pin-JTAG port is made use of as the input for the acquisition signal, and the acquisition input has 8 channels. In order to ensure the stability and flexibility of the signal, a differential input method is applied. A total of 16 ports are used to connect into the acquisition electrode lines. Apart from the power and ground ports, the remaining two ports are the reference terminal and the right leg drive input terminal.
The acquisition circuit is based on the ADC ADS1299, which is an AD chip specially applied to collect bioelectric signals. It brings the merits of 24-bit resolution, high accuracy, and low noise. It is able to

acquire simultaneously in multiple channels as well. The device is in the form of a triangle integral. Both the crystal oscillator and the reference voltage are internal designed, and a programmable gain amplifier (PGA) is built in, so the acquisition accuracy, reliability and stability are obvious.

2.3.3. Wireless communication. We selects the USR-C322 chip produced by TI company, and the internal single-chip microcomputer CC3200 is a single-chip microcomputer based on the Cortex-M4 core. This chip is an industrial-grade WIFI module, which is a low-power wireless communication chip designed to implement embedded system design. Various information of the ADC, power management module, and battery monitoring chip are transmitted to the module through SPI or I2C bus, and then connected to the same network with the PC, that is, in a networking state, and all information is transmitted to the host computer to process.

2.3.4. Interference suppression and electrostatic protection. In order to reduce the interference of high-frequency signals like the WIFI on hardware circuits, we have prevented capacitance effects during wiring, and paid attention to digital-analog separation during overall layout. Meantime, we use the TPD6E001, which is a chip specifically designed to reduce electrostatic interference, because the power supply is a positive and negative power supply design. After connecting the input and output terminals to the chip, it will reduce the impact of static electricity and the input voltage is kept within $\pm3.3V$, which can protect the device from being damaged by large voltage shock.

2.3.5. Technical indicators Analysis. The technical indicators of the designed EMG signal acquisition device are shown in Table 1. The indicators to be analyzed are: the accuracy of the EMG signal acquisition, system stability, and endurance. As described in Section 2.3.1, the lithium battery can work for 13 hours at maximum power and up to 24 hours in normal mode, and the choice of this battery can be changed at any time. A battery with a higher capacity can be selected to provide power for super long battery life.

Table 1. The technical indicators of the designed EMG signal acquisition device.

Biosignal	Precision	Resolution	Sampling rate
sEMG	5μV	24 bits	1000Hz

When acquiring weak analog signals like sEMG signals, the quality and purity of the obtained signals is very important. In the case of maximum wireless power, we set the sampling rate to 1kHz, set the PGA amplification factor to 6 times, and short the analog positive and negative input terminals. At this time, the device will collect the interference signal, and the average peak-to-peak value of the interference noise is about 0.68μV, and even in the case of strong interference, the maximum peak-to-peak value is only about 4.29μV. After 6 times amplification of the EMG signal, the interference noise can be almost ignored. Considering the system noise without voltage input is 5μV and the amplitude of the EMG signal is 5mV, the SNR can be calculated to be 60dB.

In order to ensure the stable and reliable data transmission process and reduce the power consumption of the acquisition device, the format of the data communication needs to be set. The length and format of the EMG data collected in this paper are shown in Table 2.

Table 2. The technical indicators of the designed EMG signal acquisition device.

Type of data	Composition way	Total length (Byte)
sEMG	3Byte/channel	3×number of channels

Considering the Udp transparent transmission protocol, the data packet format of the entire acquisition system is shown in Table 3.

Table 3. Packet format.

Parameter	Start	Packet number	Status	Test data	End
Length (Byte)	2	2	3	< 220	2

The data packet needs a start of 2 byte length for unpacking processing. The 2 byte packet number is of unsigned int type, so the maximum value is 65536. If the sampling rate is 1kHz, it will be cycled in about half an hour. The status is used to determine the status of the device. The connection, communication, disconnection, and remaining battery power are determined by this status bit. The length of the test data is selected to be less than 220 bytes to ensure that the packet protocol is still valid when the sampling setting is changed, and does not exceed the range. And it is convenient to reserve 10 byte space for future extension function. The end of the byte is used to end the transmission. It can be seen that the length of the data packet is ultimately controlled by the host computer software.

The stability of the communication means how long the EMG signal acquisition process can be maintained. After 5 experiments with the acquisition device working in the acquisition state, it was found that each experimental device worked normally until the battery power was zero. The working position was 5m away from the host computer and the working time was about 13 hours, which could prove that the acquisition equipment has good stability.

2.3.6. Acquisition device testing and analysis. For the sake of portability and easy operation, the wearable hardware acquisition device is as simple as possible to simplify the scale of the hardware circuit. The appearance is shown in Figure 2. The signal acquisition device is a rectangular box with a size of 6.4cm * 3.7cm * 1.7cm, with the built-in signal acquisition board and the 3.7V Li-ion battery. It is clear that this circuit is highly integrated and it is very convenient to collect physiological signals. The signal is acquired by connecting the collection electrode line made by 20pin-JTAG to the patch electrode. It is equipped with a Micro-SD card slot for storing offline data. The signal is continuously acquired over time and saved for subsequent processing and analysis.

After the hardware circuit is connected to the acquisition platform of the PC, the collected physiological signals can be displayed in real time by waveform in the software. After the signals can be effectively acquired, sEMG are collected according to a preset sample length. Then features in collected samples are extracted to form a eigenvector set and input to the network for classification training. The classification result of the gesture of the classifier is set to 1, 2, 3, 4, and 5 respectively, corresponding to fist clenching, hand opening, wrist flexion, wrist extension, and gesture of No. 6. The static action corresponds to 0 alone, because the static action is calculated as threshold for determine whether there is an action, so it is not counted as a classified action. The waveform is shown in Figure 3.

3. Signal processing

3.1. Preprocessing, feature extraction and classification

We chose the median filtering whose window length L = 11 to to remove baseline wander of the raw signal. Butterworth notch was selected to remove power frequency interference. The stopband frequency was 49-51Hz, passband attenuation was $r_p = 1$dB and the stopband attenuation $r_s = 50$ dB. Chebyshev filter was chosen to get rid of high frequency interference. The passband frequency was 10-300Hz and the filter order was 256.
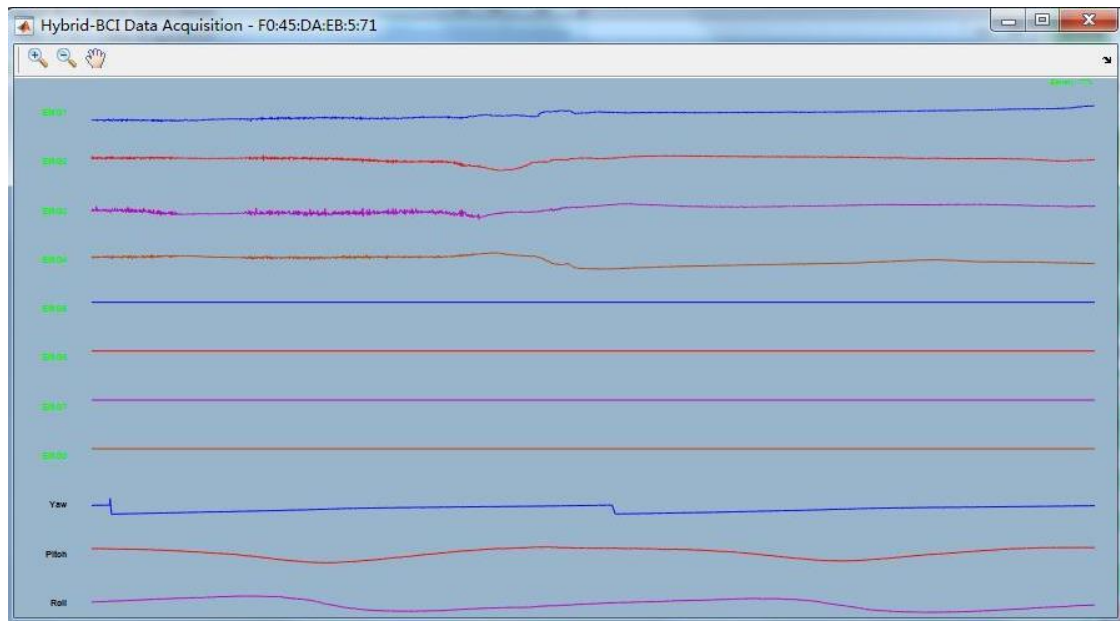
Figure 3. The real-time waveform display.

After preprocessing, feature extraction is required. Despite the EMG signal belongs to a non-stationary random one-dimensional biosignal, it is able to be taken as a stationary random signal in a short time. After many experiments and training, we selected three feature values: mean absolute value (MAV), root mean square (RMS), and waveform length (WL) [7] to perform gesture classification training. These three features was extracted from each channel. The BP neural network was selected to perform pattern recognition on the extracted features. A three-layer network was determined for classification training, that is, the hidden layer is determined as one layer. It was found that when the number of hidden layer nodes was 9, the training speed was the fastest and the recognition rate was the highest. The complete network is set to a 12-9-5 structure. The input node corresponds to a total of 12 dimensions of the 4 channels, and the output node corresponds to the 5 gestures to be identified.

3.2. Analysis of overlapping sliding windows

The signal needs to last for a long time in the acquisition process. If this long time is spent in the real-time control phase, it will definitely cause a great delay in the change of movement. Therefore, the signal needs to be divided into a series of small windows for processing. In addition, when the sEMG signal is used to recognition gesture for control the bionic manipulator, if the recognition system receives a long continuous sEMG signal, the processing speed will be reduced, and the subject will experience a significant action delay. So the overlapping sliding window method is applied to process the signal in real-time. In fact, the whole signal processing, feature extraction, classification are realized in sliding window to achieve real-time control of the bionic manipulator.

3.3. Real-time control

In order to control the manipulator to make the same gesture as a human hand, first we saved the steering angle command of the manipulator corresponding to the movement, and then set the label of each gesture to the output of the BP neural network. Then, a label corresponding to the gesture was output, and then the program sent a robot motion instruction statement corresponding to the label to the manipulator through a serial port, and then it can be controlled to make a corresponding gesture.

4. Experiment

4.1. Experimental procedure

Before the experiment, the subjects cleaned their arm with alcohol, and kept their sitting postures. A layer of conductive adhesive on the skin surface was put and the electrodes were fixed. Then the operator connected the acquisition device and electrodes with data acquisition lined. During the experiment, MATLAB software was used to monitor the surface EMG signal changes in real time. During the acquisition process, the forearm of the subjects was flat on the table, the action intensity was moderate and the consistency between the same action patterns was kept as much as possible. Each gesture need be collected 6 times, each time was 12s, that is, one gesture cost 72s.

This paper designs 5 types of gestures that need to be identified based on people's daily habits: fist clenching, hand opening, wrist flexion, wrist extension, and gesture of No. 6. The software applies the Matlab platform and integrate functions of equipment communication, signal acquisition and processing, real-time control, etc., to facilitate integrated operation. The acquisition aspect involves establishing connection, adjusting preset parameters, showing waveform in real time and saving. The algorithm is designed in biomedical signal processing, model training and a real-time control. The device sends the collected data to the PC software through the network. Then the signal is processed (median filtering, notch, bandpass filtering), and the features are extracted for network training. The trained network is able to be stored. After the training network is in order, the data collected will be sent into the network and made comparison with the trained data directly. Next, the classification label for gestures are generated. Finally, these labels are turned into the corresponding gesture code sequence. The bionic manipulator can make corresponding gestures in real time by sending code sequence to the manipulator via the serial port. The flow is shown in Figure 4.

The individual accuracy and average accuracy of the five gestures pattern recognition of the four subjects are counted. The experiment was performed for three days, i.e., a complete experiment was performed every day. Taking the Subject #1 as an example and the results are shown in Table 4.

Table 4. The accuracy of Subject #1 among 3 days.

Gestures	Fist clenching	Hand opening	Wrist flexion	Wrist extension	Gesture of No.6	Average
Day 1	100%	90%	90%	92%	76%	87.6%
Day 2	100%	100%	100%	96%	66%	92.4%
Day 3	100%	90%	92%	96%	86%	92.8%

The tendency of the average accuracy of the four subjects is shown in Figure 5. the x-label is the experimental days and the y-labels is the average accuracy. The exact data are listed in Table 5.

Table 5. The average accuracy of subjects among 3 days.

Subjects	Day 1	Day 2	Day 3
#1	87.6%	92.4%	92.8%
#2	81.2%	85.4%	92.0%
#3	83.4%	87.8%	91.2%
#4	80.4%	88.2%	90.6%

5. Discussion and Conclusion

It can be found from Table 4 that although the accuracy of some gestures increases or decreases with the number of training days, the overall accuracy improves. The recognition rate of the fist clenching has always been 100%. It can be known that this action is the easiest to distinguish. It can be seen that after the number of training days of the four subjects increases, the average accuracy rate of gesture

classification also shows an upward trend, so the accuracy rate can be improved through multiple experiments and increasing the number of experimental days.

The sliding window method and real-time control calculation contribute to the performance of the real-time control. The entire process takes less than 200ms, which is less than the acceptable delay time of 300ms, so it fully meets the requirements of the delay time. The manipulator generates gestures quickly, almost synchronizing with the hands of the subject. Therefore, our design is effective and reasonable.
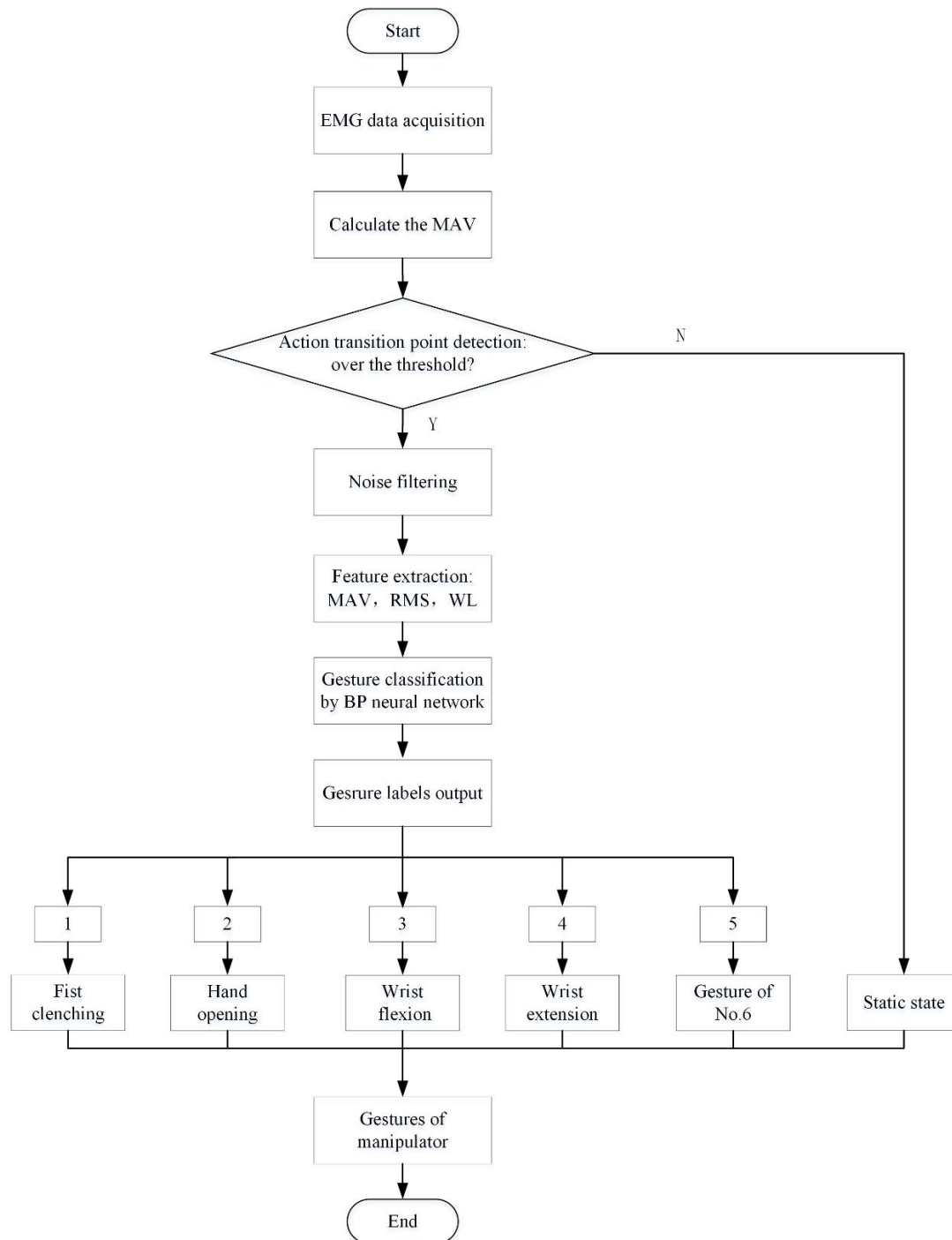

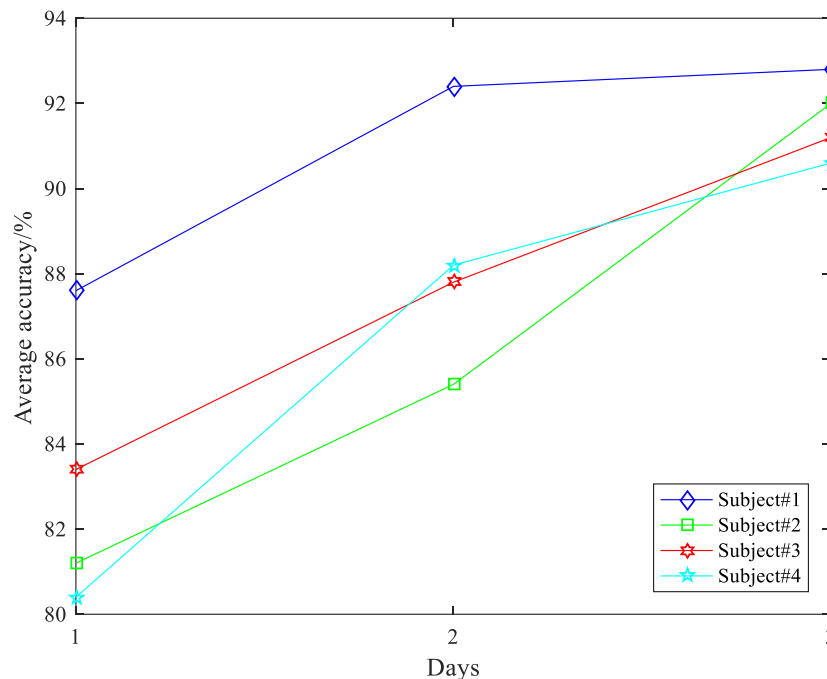**Figure 4.** The whole flow of real-time control.

Figure 5. The tendency of the average accuracy.

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