A Study on EMG Signal Classification for Improving Control Methods for Electric Prosthetic Hands

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Abstract

In general, it is difficult to recognize EMG patterns for controlling prosthetic arms because they are not fixed and vary greatly in characteristics. In this paper, we evaluate the classification ability of root mean square, integral, and power spectral densities to identify various hand motions including wrist flexion, extension, wrist adduction, abduction, grasping, and abduction. To perform this study, EMG signals are measured in the finger extensors, carpal tunnel extensors, carpal tunnel flexors, and carpal tunnel flexors. EMG signals are analyzed for root mean square, integral and power spectral density. Through experiments, it was shown that the proposed method can estimate hand movements efficiently.

Keywords
EMG signals, EMG patterns, finger extensors, hand motions and prosthetic arms.

1. Introduction

1.1. Research Purpose

In this paper, various control methods were used to solve the user's inconvenience and various control methods caused by using an acupressure point switching device as a control signal in previous studies on mechatronic prosthetic arms with a light and foldable structure. By analyzing and improving the patterns of EMG signals, it can use signals from the body's muscles known as one of the most effective control methods. Develop a mechatronic prosthetic hand with a foldable structure that can replace the arm function of a brachial amputation patient, and study a more convenient EMG control method suitable for multi-degree-of-freedom multi-lateral control. I want to show a functional prosthetic hand, but I have a purpose.

Therefore, the first research direction focused on the design and construction of an analysis system for EMG acquisition for prosthetic hand control, and the second research direction aimed at a classification method of EMG signals to distinguish each motion from a practical point of view.

1.2. Automated Prosthetic Research

After World War II, much research was conducted to develop prosthetic arms for many people with disabilities due to the war. In 1961, Wiener (1961) proposed the possibility of using biosignals to control mechanical devices, and Reiter (1948) proposed EMG signals or EMG signals, which are minute voltage signals generated during muscle contraction. Since hand control was developed, continuous development attempts have been made by a small number of research groups or schools.

A brief look at the situation in which artificial automatic prostheses operated by an external power source have been studied is as follows. Since 1950 IBM Arm of Alderson (1968), Russian EMG Control Hand of Popov (1965), Viennatone Hand of Peizer et al. (1969), Boston Elbow of Rothchild and Mann (1966), and Jerard et al. (1974), Otto Bock Hand of Peizer et al. (1969), Fidelity Hand of Product Literature and Childress (1972), Italian Arm of Schmidl (1973), Utah Arm of Jacobsen et al. (1975), and Swedish Arm, many automatic prosthetic arms were developed in the United States, Japan of Funakubo et al. (1980), and Europe. Among them, Utah Arm and Otto Bock Hand are the most advanced automatic prosthetic arms that have been successfully commercialized. By moving the disabled person's joints, they can perform simple movements on their own.

1.3. A Study on Control using EMG Signals

An attempt to use myoelectric signals from the muscles of the human body as an effective way to control an artificial automatic device operated with an electrical external power source has been proposed by many researchers and is being widely used in practice. The first known use of electromyographic signals was in 1948 when Reinhold Reiter tested an electromyographic prosthetic hand made for use by factory workers. However, research in this early period was not active, but around 1969 interest was revived and research was revived. From this time, independent research began in the former Soviet Union, England, Sweden, Japan, the United States, Canada, etc. to develop an automatic prosthetic arm or leg using EMG signals. Currently, many automatic prosthetic arms that have one degree of freedom (movements of the hand, wrist, and elbow) and use EMG as a control signal have been commercialized and put into practical use. Such a prosthetic hand obtains a control signal using the amplitude or rate of change of the EMG signal, and usually obtains the control signal using one muscle group or two muscle groups. If a control signal is obtained using only one muscle group, the amplitude of the EMG signal determines the operating state of the device. A method of determining the state of an element with a signal of amplitude is widely used. When an operating state is selected, the speed at which the prosthetic arm is operated can be set constant or adjusted according to the magnitude of the force applied when the muscle contracts and the amplitude of the EMG signal that increases or decreases in proportion thereto. Although these methods are successful in controlling a prosthetic hand with one degree of freedom, they have been considered unsuitable for controlling a prosthetic hand with many degrees of freedom or a multifunctional prosthetic hand that requires many control signals. The reason is that many control signals are required to drive a multi-functional prosthetic arm with multiple degrees of freedom. In order to generate these multi-control signals, you end up attaching many sensors to different muscle groups. However, in reality, there is a limit to selecting a muscle group to be used as a signal source, and controlling the prosthetic arm by applying force to various muscle groups is a very inconvenient manipulation method. Therefore, by focusing on the problem of generating various control signals while reducing the number of signal-generating muscle groups, research on the development of EMG control methods suitable for multi-functional assistive devices with multiple degrees of freedom is being actively conducted. In fact, studies that allow one muscle group to control more than one degree of freedom are as old as the history of assistive devices using EMG signals. Reiter wanted to choose a motion that would allow one muscle group to control the two movements of opening and closing the hand.

In general, one-degree-of-freedom prostheses that have been commercialized so far often choose a method of adjusting the prosthetic arm by appropriately contracting two muscle groups, flexors and extensors. However, using two muscle groups to control one degree of freedom is a waste of muscle groups in that it controls a prosthetic hand with multiple degrees of freedom. So Dorcas and Scott (1966) developed a Three-State Single-Site Control method, similar to the method used by Reiter, allowing one muscle group to control the device with one degree of freedom (three states including rest) proposal. However, with the advent of microcomputers, sophisticated experiments on the EMG signal itself and sophisticated control of the prosthetic hand became possible, and new EMG control methods began to be announced. Graupe et al. (1975~78) proposed a method called Time-Series Identification Procedure that classifies EMG signals into classification patterns already divided into several types according to the characteristics of EMG signals. it will be However, this method has a disadvantage in that the time required to generate the control signal required for the natural motion of the prosthetic hand is not fast. Wirta et al. (1975) used a method using many electrodes to form a pattern representing the spatial distribution of the time integral of the EMG signal. Meanwhile, a method using statistical analysis of EMG signals was developed by Newman and Saridis and Newman (1979). They classified the shape of muscle contraction posture determined from the feature space of the variance and zero crossing of the EMG signal, and determined from which muscle contraction posture the received EMG signal came from. Besides this, many other important studies on automatic prosthetic control technology were conducted by Lyman and Freedy et al. (1972~74), Lawrence and Lin (1972) and Jacobsen et al. (1973, 1982). Recently, Hudgins et al. (1993) proposed a novel method for controlling assistive devices with multiple degrees of freedom. At the beginning of muscle contraction, various types of signal waveforms are generated according to the type of muscle contraction posture. After discovering this, a waveform that appears at the beginning of muscle contraction was generated through a pattern identification process using a neural network, and an appropriate control signal determined according to the characteristics of the waveform was generated. Although the results of previous studies have yielded theoretical and practical results in controlling assistive devices, there is a continuing need for a faster and more stable EMG signal recognition process (development of identification procedure) that recognizes more accurate information about movement or speed from EMG signals. . It achieves the ultimate goal of developing an automatic prosthetic arm or prosthetic arm that enables disabled people to freely perform various functions with minimal effort like ordinary people.

2. Body

2.1 Hardware Configuration

The hardware configuration of the EMG signal measurement system consisted of a power supply unit, a sensor unit using Ag/Agcl surface electrodes, an amplification and filter unit, and an A/D conversion unit, and the hardware was controlled using software. Figure 1 is a hardware flow diagram for EMG signal measurement.

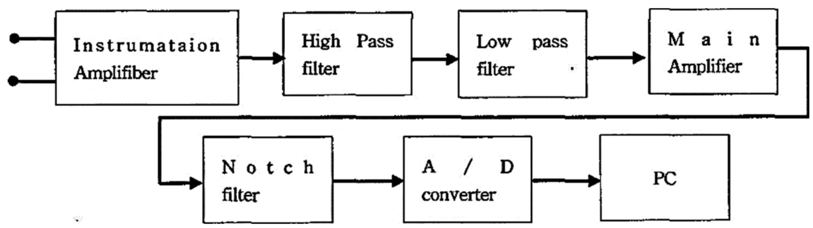

Figure 1. Overall flow diagram of the hardware system

2.2 EMG Signal Measuring Unit

EMG signals are measured through four channels. EMG signals from 4 muscles of the forearm were converted into electrical signals during 6 movements and measured.

Electrodes for EMG signal recording have various shapes and structures. In order to detect the current generated by the movement of ions within the muscle, the electrode must first be harmless to the human body and make good contact with the muscle. The area of the electrode that electrically contacts muscle tissue is called a detection surface, and the size of the detection surface is important for recording and analyzing EMG signals. If the detection surface is small, muscle activity in a narrow area can be measured, and if the detection surface is large, muscle activity signals in a wide area can be overlapped and measured. Electrodes can be divided into recording electrodes, stimulation electrodes, and ground electrodes according to their functions. The recording electrode refers to an electrode used to measure muscle activity, and the stimulating electrode is an electrode used to stimulate nerves in order to observe a response to stimulation, unlike the recording electrode. In addition, the ground electrode is an electrode used for the purpose of defining a potential as a reference for a recording electrode, and is usually attached to the skin without muscle activity.

According to the measurement method, the electrode that measures the muscle activity at one point with the ground electrode as the reference potential is called a unipolar electrode, and the electrode that measures the difference in muscle activity at two points based on the ground electrode is called a unipolar electrode. bipolar electrode. However, since unipolar electrodes are vulnerable to power supply noise, bipolar electrodes are mainly used.

Depending on the shape of the electrode, electrodes that measure by contacting the skin are called surface electrodes, and needle-shaped electrodes that are directly inserted into muscle fibers are called needle-type electrodes. Surface electrodes and needle electrodes are used separately according to the measurement site or measurement purpose. The needle electrode has the advantage of excellent resolution, but the surface electrode has the disadvantage of pain and risk of infection because it is directly inserted into the muscle. Of course, since surface electrodes are electrodes that measure signals by contacting the skin, they have a disadvantage in that they cannot measure the activity of muscles located in the deep part. It has limited characteristics for measured and precise EMG signal analysis. However, recently, studies to compensate for these limited characteristics using multi-channel surface electrodes have been actively conducted, and many developments have been made.

2.3 Analog Signal Processing Unit

The electrode used in this study was Medtronic's 9013L0452 Disposable Surface Electrode, and the electrode contains a differential amplifier with a gain of 10 times, so it has excellent noise characteristics.

The output of the electrode was used as the input of Laborie's UDS-110-12V EMG amplifier. The output signal of the EMG amplifier was sampled at 1000 Hz through NI's DAQPad-1200 A/D converter with 12-bit resolution and recorded to a parallel interface computer.

The amplifier operates at ±12V and consists of a 10Hz high-pass filter, a 2KHz low-pass filter, and a 60Hz band notch filter to remove power noise from the characteristics of the EMG signal. It is isolated for use as a target and the amplification is adjustable from 9300x to 240000x.

The final processed value was adjusted so that the value could be output within this range, considering the input voltage range of the A/D converter, 0V to 5V. Figure 2 is a circuit diagram used for analog signal processing.

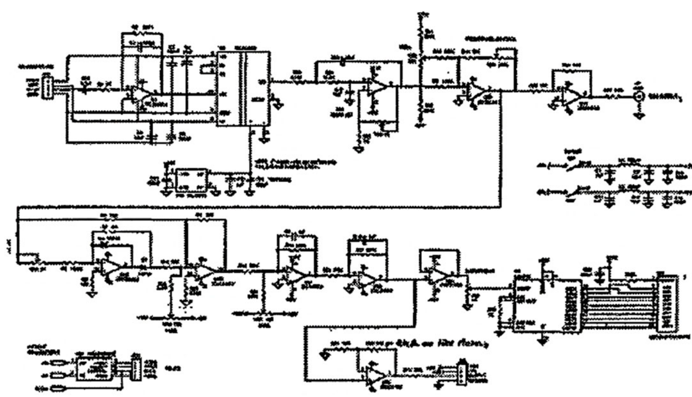

Figure 2. Analog signal processing schematic.

2.4 Digital Signal Processing Unit

The digital signal processing device used in this study was the existing DAQPad-1200. This transducer has a maximum resolution of 4096 bps with 12 bits of resolution. The input voltage range is 0 to 5V. The conversion time of 12 bits is 8.5ns, and A/D conversion can be set to 8-channel single-ended mode or 4-channel differential mode, and this system uses differential mode.

Data after A/D conversion generates 12-bit frames and transmits them to PC through Parallel Bus.

2.5 Software Configuration

In this study, National Instruments LabVIEW 7.1 was displayed on a PC and the acquired signals were analyzed through Signal Processing. Each input was received on 4 channels by 1 device, the number of samples was set to 1000, the sample rate was set to 1000 samples/sec, and no limits were set.

2.6 Experimental Process

To classify the six movements, EMG was measured in four muscles: extensor finger, extensor carpal tunnel, flexor carpi radialis, and flexor carpal tunnel muscle (Figure 3). The reproducibility of the signal measured by the EMG measurement system was reviewed through 10 repeated experiments for each of the 6 motions defined above, and the EMG of each muscle was measured in 4 channels according to the motion to examine whether it was possible to distinguish them. An electromyographic measurement experiment was conducted to obtain data that can be analyzed by a physical analysis method.

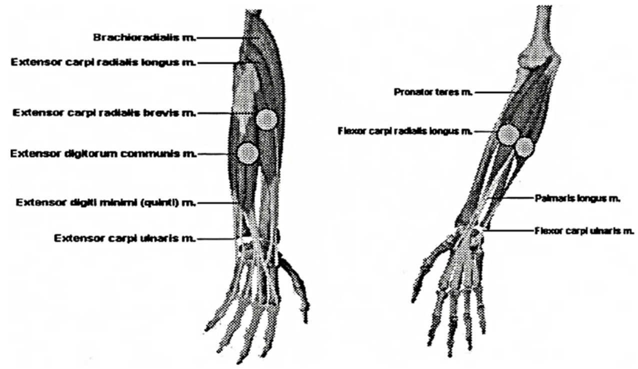

Figure 3. Muscles of EMG measurement

2.7 Experiment

In order to obtain signals from the same muscle, four sensors were first attached to each muscle, and then the difference in signal based on the brachial muscle was measured by the noise-resistant bipolar electrode method. In order to determine motion, the length of the EMG data window and the motion increment must be set appropriately. EMG is measured at a sampling frequency of 1000 Hz with preprocessing limited to 10 to 500 Hz. The window length of the data is 256 msec and the shift increment is 128 msec. The obtained data was measured by an amplifier that monitors the shape value of the EMG waveform for each muscle through software and divides the size value of the waveform into 10 steps to view it in hardware. Figure 4 shows the EMG measurement system, and Figure 5 shows the EMG measurement experiment state through the subject. Figure 6 shows the movement of muscles located in the forearm.

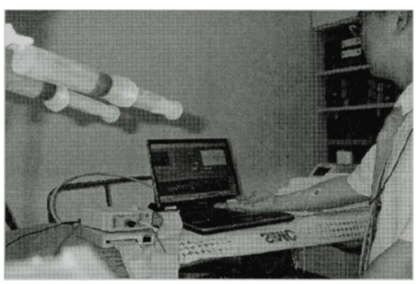

Figure 4. The EMG measurement system

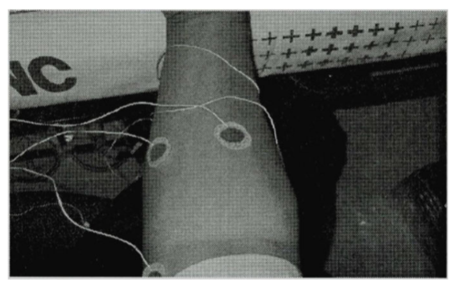

Figure 5. The EMG measurement experiment

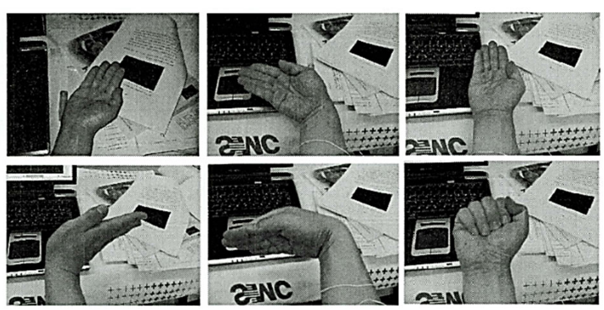

Figure 6. Movement of muscles located in the forearm

2.8 Experiment Result

The EMG measurement system used in this study measured each EMG signal from 4 muscles during 6 movements, and the amplitude of the waveform during a sampling rate of 256 msec is shown in Figure 7.

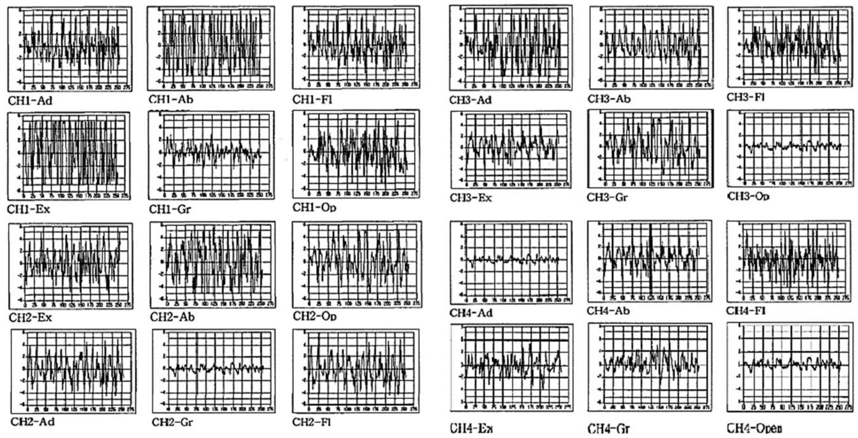

Figure 7. EMG waveforms of muscles by motion

In addition, by using various physical analysis methods for the acquired EMG waveforms, the waveforms were classified in three ways in addition to visual comparison. First, it is a method of determining the size of a waveform using an LED bar supported by hardware in the EMG amplifier used in the experiment. Second, it is a method of obtaining and comparing the integral value and the effective value of each EMG signal in the time domain. Third, the method in the frequency domain. In order to compare the features, the PSD value was obtained and it was investigated whether each signal could be easily distinguished. Table 1 shows PSD waveforms for comparing characteristics in the frequency domain with values obtained by comparing the integral value, which is the EMG signal value, in the time domain with the RMS value in Table 3.

1) Waveform Size by Muscle (LED steps)

Hardware level classification of EMG signal using LED bar In the AD Converter LM3914 included in the amplifier, it is determined whether the signal level for each operation can be distinguished using the 10-step LED bar displayed according to the level of the EMG signal. Table 1 shows the size of the EMG waveform by digitizing the displayed LED bar in 10 steps from 1 to 10 is a waveform, and if cells are classified by color, it can be seen that each channel can be distinguished according to motion.

Table 1. Waveform size by muscle (LED steps)

	adduction	abduction	Flexion	extention	grasp	open
CH1	2	3	2	10	2	0
CH2	1	8	2	10	0	0
CH3	6	2	6	3	5	0
CH4	2	2	7	2	6	0

2) Comparison using Integral Value

In order to quantify and compare the size of the waveform, the integral value of the same section was obtained for 256 msec using a program as shown in Figure 4-6. The Integral function used is:
The integral F(t) of a function f(t) is defined as

$$F(t) = \int f(t)dt$$

Let y represent the sampled output sequence Integral X. The Integral x(t), VI obtains the elements of y using

$$y_i = \frac{1}{6}\sum_{j=0}^{i}(x_{j-1} + 4x_j + x_{j+1})dt$$

for i = 0, 1, 2, …, n-1, where n is the number of elements in X, x-1 is specified by initial condition when i = 0, and xn is specified by final condition when i = n-1.

It can be seen that Table 2 shows very similar results when compared with the size values of the waveforms for each muscle using the LED bar in Table 1. In the experiment, it was confirmed that the range of change of the value was large depending on how the integration section was selected.

Table 2. Table of integral values of waveforms for each muscle

	adduction	abduction	Flexion	extention	grasp	open
CH1	4.9	6.5	28.7	29.9	20.8	0
CH2	1.4	9.2	10.6	111.2	11.8	0
CH3	20.9	55.2	79.6	28.3	40.1	0
CH4	6.4	4.1	80.0	22.5	18.1	0

3) Analysis using RMS values
As another method to quantify and compare the size of the waveform, the RMS values for 256 msec of the same section were compared. The RMS function used is as follows.

$$\Psi_x = \sqrt{\sum_{i=0}^{n-1} x_i^2 \frac{1}{n}}$$

where ψ x, is RMS value and n is the number of elements in X.

The same result was confirmed by comparing the RMS value of each muscle waveform in Table 3 with the analysis table and the magnitude value of the EMG waveform.

Table 3. RMS value analysis table of each muscle waveform

	adduction	abduction	Flexion	extention	grasp	open
CH1	1.54	1.68	1.78	3.65	0.62	0
CH2	1.83	2.48	1.58	3.52	1.2	0
CH3	2.07	1.59	2.17	2.15	1.61	0
CH4	1.37	0.45	2.12	0.92	1.24	0

4) Analysis using PSD values
As another way to quantify and compare the size of the waveform, the PSD values for 256 msec of the same section were compared. Table 4 is a PSD value analysis table of each muscle waveform.
The Power Spectrum Sxx(f) of a function x(t) is defined as

$$S_{xx}(f) = X*(f)X(f) = |X(f)|^2$$

where X(f) = F{x(t)}, and X* (f) is the complex conjugate of X(f).
The Power Spectrum VI uses the FFT and DFT routines to compute the power spectrum, which is given by

$$S_{xx} = \frac{1}{n^2 |F\{x\}|^2}$$

where Sxx, represents the output sequence Power Spectrum, and n is the number of samples in the input sequence X. When the number of samples, n, in the input sequence X is a valid power of 2n = 2m for m = 1, 2, 3, …, 23,

Table 4. PSD value analysis table of each muscle waveform

	adduction	abduction	Flexion	extention	grasp	open
CH1	-7.99	-4.9	-9.6	1.16	-6.32	0
CH2	0.27	5.4	-0.79	7.76	-9.77	0
CH3	3.22	-6.1	10.44	-10.44	0.08	0
CH4	-1.55	-12.58	2.86	2.86	-7.38	0

3. Conclusion

In this study, a folding mechanism developed for the wrist amputee who needs a prosthetic hand was studied to operate according to the classification of EMG signals to use as an effective method for controlling the prosthetic hand. The system for EMG analysis used in this study enabled monitoring by accepting EMG signals from four muscles. EMG signals were measured in each channel during 6 types of motion. By measuring signals from four muscles for each motion and classifying the signals, it could be used as an effective signal for controlling the prosthetic hand. It was confirmed that it is possible to implement the control method.

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Biography

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