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Prosthetic Hand Control using Motion Discrimination from EMG Signals

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Abstract—**In this report, we improve the motion discrimination method from electromyogram (EMG) for a prosthetic hand and propose prosthetic hand control. In the past, we proved that a motion discrimination method using conic models could discriminate three hand motions without the incorrect discriminations that the elbow motions cause. In this research, to increase discrimination accuracy of motion discrimination using conic models, we propose a feature extraction method using quadratic polynomials. Additionally, because many prosthetic hands using motion discrimination have constant motion speed that can't be controlled, we propose an angular velocity generation method using multiple regression models. We verified these methods by controlling the 3D hand model. In the experiment, the proposed method could discriminate five motions at a rate of above 90 percent without the incorrect discriminations that elbow motions cause. Moreover, the wrist joint angle of the 3D hand model could be controlled by standard variation of 3[deg] or less.**

I. INTRODUCTION

Myoelectric prosthetic hands, which are controlled by electromyogram (EMG) signals, have the good functionality and visual quality. However, many myoelectric prosthetic hands can perform only two motions (opening and gripping of the hand); they perform one motion when one muscle contraction, such as opening when the wrist extensor muscle contracts and closing when the wrist flexor muscle contracts. Moreover, myoelectric prosthetic hands must be adjusted to users because EMG signals vary by individual. To improve myoelectric prosthetic hands, it is effective to apply the methods that can automatically adjust prosthetic hands to users by learning EMG signals and can discriminate a hand motion by the signals for controlling it. Many researchers have studied the discrimination methods [1]-[4]. In these cases, artificial neural networks are commonly applied because they can consider the nonlinearity of EMG signals, but these methods take a long time to learn the EMG signals.

Considering this point, we proposed a hand discrimination method using linear multiple regression models [5]. This method doesn't consider the nonlinearity of EMG signals, but it learns EMG signals quickly. We proved that three hand motions (open, close and chuck) can be discriminated by EMG signals measured from the forearm. However, many myoelectric prosthetic hands using motion discrimination incorrectly discriminate elbow motions as a certain hand motion. In previous research, to solve this problem, we proposed a hand discrimination method using conic models, which can learn EMG signals in real time. We proved that the proposed method could discriminate three hand motions from EMG signals without the incorrect discriminations that the elbow motions cause [6].

In this research, to increase the discrimination accuracy of conic models, we propose a feature extraction method using quadratic polynomials. A quadratic polynomial extracts a feature of a motion to project EMG signals into feature space that makes them easier to discriminate. In addition, to control the motion speed of the prosthetic hand, we propose an angular velocity generation method using multiple regression models. Since many prosthetic hands using motion discrimination have constant motion speed that can't be controlled, this is unnatural compared with human hands.

We verify these proposed methods by controlling a 3D hand model on a PC. In the experiment, we verify the discrimination accuracy and that the proposed method can prevent incorrect discrimination that elbow motions cause. Moreover, we verify the accuracy of the wrist angle control of the 3D hand model.

II. THEORY

Fig.1 shows the 3D Hand Model Control System. The system is composed of the feature extraction method using quadratic polynomials, the motion discrimination method using conic models and the angular velocity generation method using multiple regression models. The quadratic polynomial extracts a feature of a motion from EMG signals measured from the forearm. The conic models discriminate the motions from the features. Discriminated motions are hand motions (open, close and chuck) and wrist motions (extension and flexion). At the same time, the multiple regression models generate an angular velocity corresponding to the wrist motions from the EMG signals. When a hand motion is discriminated, the hand function of the 3D hand model is switched. When a wrist motion is discriminated, the wrist joint of the 3D hand model is controlled by generated angular velocity corresponding to discriminated motion.

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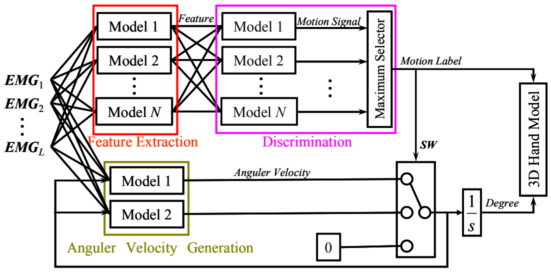
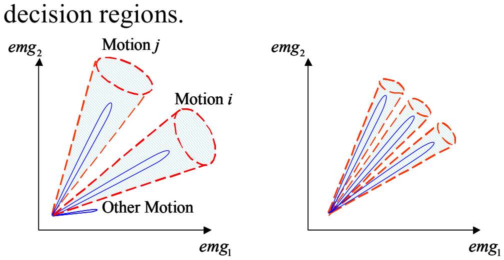


Fig. 1 3D Hand Model Control System

A. *Feature Extraction*

Fig.2(a) shows an example of decision regions for conic models in feature space in the case of discriminating motions *i, j*. In Fig.2(a), shaded regions are decision regions corresponding to motions *i, j,* dashed lines are boundaries of decision regions, and solid lines are trajectories of EMG signals when motions are performed. As shown in Fig.2, the trajectories start and leave from near the original point then return to this point because EMG signals are weak when muscles don't contract and become strong when muscles contract. The top of the cone is the amplitudes of EMG signals when muscles don't contract and the cone-shaped decision region is located in such a way as to wrap a trajectory corresponding to motions *i*, *j*. Because the trajectories corresponding to elbow motions are greatly away with trajectories of discriminated motions, the conic models prevent incorrect discriminations about elbow motions. However, as shown in Fig.2(b), decision regions become small in the case of discriminating motions with similar trajectories. Consequently, quadratic polynomials project trajectories of motions into the feature space that has large enough decision regions.



(a) (b)

Fig. 2 Examples of Decision Regions using Conic Models

1) Quadratic Polynomials: The quadratic polynomials extract a feature of each discriminated motion from EMG signals. The feature corresponding to a motion takes the biggest value when the motion is performed. Every motion model using the quadratic polynomials is modeled.

A feature fq_i using the quadratic polynomials corresponding to motion *i* is expressed by the quadratic polynomials from amplitudes of EMG signals that are full-wave rectified and smoothed after being measured from *L* channels:

$$fq_i = \sum_{l\le m=1}^{L} a_{ilm}\, emg_l\, emg_m + \sum_{l=1}^{L} b_{il}\, emg_l + c_i \tag{1}$$

where a, b and c are coefficients. These coefficients are presumed by the least squares method using a target signal that is generated by a method described later.

2) Generation Method of a Target Signal: A target signal is needed when presuming coefficients by the least squares method. The generation of target signal ts_n is described as follows. Each motion is performed once, and sum *S* of the EMG signals of each channel is calculated. It is assumed that there are *L* channels of the EMG signal measured and *N* motions are operated.

$$S = \sum_{l=1}^{L} emg_l \ . \tag{2}$$

Since the EMG signal produces a peak whenever a motion is operated, *S* produces *N* peaks. The *n*-th peak corresponds to the motion performed at the *n*-th. The target signal corresponding to motion *n* is calculated as follows:

$$ts_n = \begin{cases} S-e & (i=n) \\ d(S-e) & (i\neq n) \end{cases}, \tag{3}$$

where i ($i = 1, \cdots, n, \cdots, N$) is the number of peaks. *d* is a coefficient which takes the value of 0 to 1. *e* is the threshold value of *S*. While *S* falls below *e*, the target signal is generated as 0. The target signal takes the biggest value when a corresponding motion is performed. Because EMG signals can be measured and teaching signals can be calculated in real time, coefficients can be updated without learning time.

B. *Motion Discrimination*

The cone-shaped decision regions are located by conic models. The conic models generate signals that have a positive value when a certain motion for discrimination is performed and a negative value when other motions for discrimination and elbow motions are performed. In this research, these signals are called motion signals. A conic model of each motion is composed. A discriminate result is the motion corresponding to the motion signal that has the greatest positive value.

1) Conic Model: A motion signal using a conic model corresponding to motion *i* is expressed as the following equation:

$$ms_i = \sum_{n=1}^{N} a_{in}(fq_n - c_n) - \cos\omega_i \sqrt{\sum_{n=1}^{N} (fq_n - c_n)^2} \tag{4}$$

where $\mathbf{c} = (c_1, \cdots, c_n, \cdots, c_N)$ is a vector that indicates the top of a cone, $\mathbf{a}_i = (a_{i1}, \cdots, a_{in}, \cdots, a_{iN})$ is a unit vector that indicates the center line of a cone and ω_i is a vertex angle of a cone. In this research, $\mathbf{c}$ is the amplitude of EMG signals when muscles don't contract, and $\mathbf{a}_i$ is the normalized amplitude of EMG signals offset by $\mathbf{c}$ when EMG signals are at a peak by performing motion *i*. $\mathbf{c}$ and $\mathbf{a}_i$ are obtained in real time.

2) The Method for Obtaining a Vertex Angle: Vertex angle ω_i can be decided by only the positional relation of trajectories corresponding to motions for discrimination. Fig.3 shows trajectories corresponding to motions *i*, *j* and *k*. First, we calculate half angles between the center line corresponding to motion *i* and other motions. Next, we select the minimum half angle to ω_i . The above method is formulated as follows.

$$\begin{aligned} \omega_i &= \min(\theta_{ij}, \theta_{ik}) \\ \theta_{ij} &= \frac{1}{2}\arccos\left(\frac{\mathbf{b}_i \cdot \mathbf{b}_j}{|\mathbf{b}_i||\mathbf{b}_j|}\right) \quad (i\neq j\neq k) \ . \end{aligned} \tag{5}$$

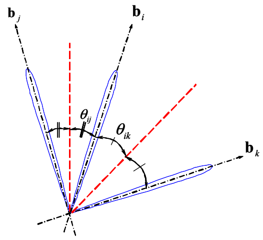


Fig. 3 Method for Obtaining the Vertex Angle of the Cone

C. Angular Velocity Generation

Multiple regression models generate angular velocities of motions. Generated angular velocities correspond to the amplitude of EMG signals when motion is performed. Angular velocity $V_{(T)i}$ corresponding to motion i is expressed as the following equation:

$$V_{(T)i} = \sum_{l=1}^{L} a_{il} emg_l + b_i V_{(T-1)i} + c_i \tag{5}$$

where a, b and c are coefficients obtained by learning. $V_{(T-1)i}$ is feedback angular velocity. Target signals are chirp signals. These coefficients are presumed by ridge regression.

III. Experiment

A. Experimental Equipment

Fig.4 shows the experimental system. EMG amplifiers (EMG-025, Harada Hyper Precision Inc.) that are amplified 500 times (54 dB) are used to measure EMG signals. Disposable electrodes built into the preamplifier are employed. EMG signals are measured in four channels from surface electrodes, and the electrodes are arranged around the forearm. The PC (Pentium IV, 2.8 GHz, 1GB) served as the host computer. The 3D hand model control system is designed using MATLAB/Simulink (dSPACE). The 3D hand model was built by MotionDesk (dSPACE). DS1005 (Power PC 800 MHz, dSPACE) and DS2002, DS2103 and DS3002 are applied for DSP, A/D, and D/A conversions.

Obtained EMG signals were full-wave rectified and smoothed by 300ms moving average for feature extraction. Angular velocity generation was smoothed by 150ms moving average, and generated angular velocity was smoothed by 150ms moving average. Furthermore, sum EMG signals have a threshold value. If sum EMG signals fall below the threshold value, motions can't be discriminated.

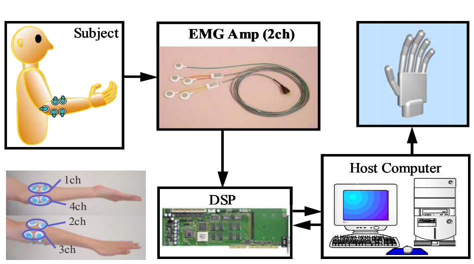


Fig. 4 Experimental System

B. Experimental Method

Subjects were five able-bodied adults (A, B, C, D, and E). Subjects A and B had previous experience with experiments. Subjects C, D, E had no experience and were trained to use the experimental system for one-two hours.

For obtaining learning parameters of quadratic polynomials, we made subjects perform motions each five times. Then, for obtaining learning parameters of conic models, we made subjects perform each one motion. In addition, for obtaining learning parameters of multiple regression models, we made subjects contract forearm muscles according to an amplitude of a chirp signal on the display.

To verify discrimination accuracies, we made subjects perform motions 30 times each, and confirmed that the proposed method doesn't incorrectly discriminate hand motions as a result of elbow motions. Moreover, to verify control accuracies of the 3D hand model wrist joint, we made subjects perform each wrist motion for the wrist angle to become the target value. In a trial, subjects performed only a wrist motion.

IV. Result and Discussion

A. Experiment Results of Motion Discrimination

Fig.5 shows an example of the features using quadratic polynomials when a subject performed motions in the following order: open, close, chuck, wrist extension, wrist flexion forearm motions, and extension, flexion, external rotation and inner rotation elbow motions. An example of the motion signals using conic models, sum EMG signals and discrimination results is shown in Fig.6, 7, 8 respectively. All features had the biggest value when the corresponding motion was performed. All motion signals had a positive value when a corresponding motion was performed, and had a negative value when the subject performed other hand motions and elbow motions.

Table I (a) (b) shows discrimination accuracies using EMG signals and features. In discrimination motions from EMG signals, some motions had discrimination accuracies below 90 percent. However, for features, all motions could be discriminated at rates of above 90 percent. Moreover, the proposed method discriminated elbow motions incorrectly as a certain hand motion.

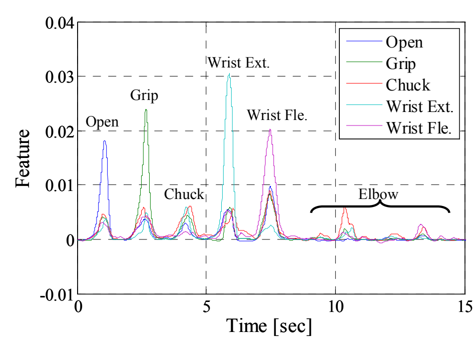


Fig. 5 Features using Quadratic Polynomials

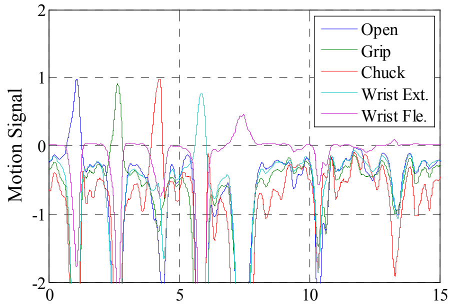


Fig. 6 Motion Signals using Conic Models

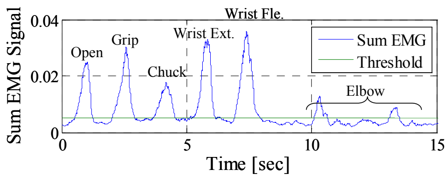


Fig. 7 Sum EMG Signals

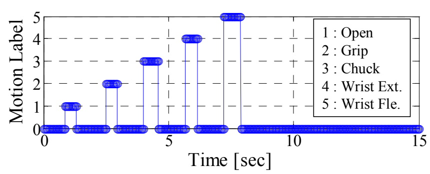


Fig. 8 Motion Label

Table I Discrimination Rates [%]

(a) Conic Models from EMG Signals

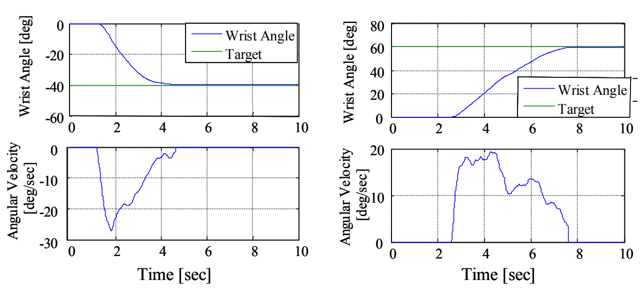
	A	B	C	D	E
open	100	96.7	100	96.7	90
grip	100	66.7	66.7	96.7	100
chuck	100	100	76.7	96.7	83.3
extension	63.3	80	56.7	100	63.3
flexion	96.7	73.3	100	100	100

(b) Conic Models from Features

	A	B	C	D	E
open	100	100	96.7	96.7	93.3
grip	96.7	96.7	96.7	96.7	100
chuck	100	100	100	100	100
extension	100	100	90	96.7	93.3
flexion	100	100	96.7	100	96.7

B. *Experiment Results of 3D Hand Model Control*

Fig.9(a) (b) shows an example of the wrist angle and generated angular velocity when a subject performed wrist extension and wrist flexion. Standard variation between target angle and final wrist angle is shown in Fig.10. According to this figure, all subjects could control the 3D hand model wrist joint by standard variation of 3[deg] or less. This result indicates that the prosthetic hand control has admissible accuracy for practical use.



(a) Wrist Extension (b) Wrist Flexion

Fig. 9 Wrist Angle and Angular Velocity

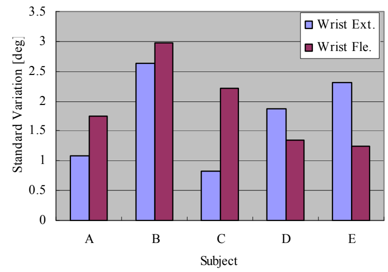


Fig. 10 Standard Variation [deg]

V. Conclusion

In this research, to increase the discrimination accuracy of conic models, we proposed a feature extraction method using quadratic polynomials. In addition, to control the motion speed of the prosthetic hand, we proposed an angular velocity generation method using linear multiple regression models. After verification, we reached the following conclusions.

1) We proposed a feature extraction method using quadratic polynomials. By this method, open, grip, chuck, wrist extension and wrist flexion can be discriminated at a rate of above 90 percent without the incorrect discrimination that elbow motions cause.
2) Discrimination accuracy using the conic model from features was higher than from EMG signals.
3) We proposed an angular velocity generation method using multiple regression models. By this method, the wrist joint angle of the 3D hand model could be controlled by a standard variation of 3[deg] or less.

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