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Forearm Motion Discrimination Technique Using Real-Time EMG Signals

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Abstract—**The objective of this study is to develop a method of discriminating real-time motion from electromyogram (EMG) signals. We previously proposed a motion discrimination method. This method could discriminate five motions (hand opening, hand closing, hand chucking, wrist extension, and wrist flexion) at a rate of above 90 percent from four channel EMG signals in the forearm. The method prevents elbow motions from interfering with hand motion discrimination. However, discrimination processing time of this method is more than 300 ms, and the shortest delay time that is perceivable by the user is generally regarded to be roughly 300 ms. Furthermore, a robot hand has a mechanical delay time. Thus, the discrimination time should be less than 300 ms. Here, we propose a real-time motion discrimination method using a hyper-sphere model. In comparison with the old model, the hyper-sphere models can make more complex decision regions which can discriminate at the state of the motion. Furthermore, this model can learn EMG signals in real-time. We experimentally verified that the discrimination accuracies of this method were above 90 percent. Moreover, elbow motions did not interfere with the hand motion discrimination. The discrimination processing time was less than 300 ms, and was about 30 percent shorter than that of the old method.**

I. Introduction

Myoelectric prosthetic hands, which are controlled by electromyogram (EMG) signals, have good functionality and appearances. However, many myoelectric prosthetic hands can perform only two motions (opening and gripping of the hand); they perform one motion when one muscle contracts, 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 individual users because the EMG signals vary from person to person. To improve myoelectric prosthetic hands, it is effective to use methods that can automatically adjust prosthetic hands to users by learning EMG signals and discriminate hand motions by the signals for controlling it. Many researchers have studied the discrimination methods [1]-[4]. Artificial neural networks have been used in these studies because they take into account the nonlinearity of EMG signals, but these methods take a long time to learn the EMG signals. Thus, it would be useful to automatically adjust prosthetic hands to users by learning the users' EMG signals and use the hand motions discriminated by the signals for controlling the limbs.

In previous research, we devised a hand discrimination method using conic models, which can learn EMG signals in real time [5]. We proved that this method could discriminate five hand motions (hand opening, hand closing, hand chucking, wrist extension, and wrist flexion) at a rate of above 90 percent from four channels EMG signals in the forearm. Moreover, elbow motions do not interfere with hand motions. However, the discrimination processing time of this method is more than 300ms. The shortest delay time that is perceivable by the user is generally regarded to be roughly 300 ms.

We propose a real-time motion discrimination method using hyper-sphere models. We verified this method by controlling a 3D hand model on a PC. We experimentally we verified the discrimination accuracy and discrimination processing time by comparing these values with ones obtained from previous models. We found that the proposed method can prevent incorrect discrimination that elbow motions cause.

II. Theory

Figure 1 shows the motion discrimination system. This system consists of processing (high-pass filter, notch filter, rectification, and moving average), feature extraction, and discriminator parts. Quadratic polynomials are used to extract the features of the discriminated motions from the processed EMG signals. Conic and hyper-sphere models discriminate five motions by using the extracted features. The feature extraction using the quadratic polynomials increase the discrimination accuracy.

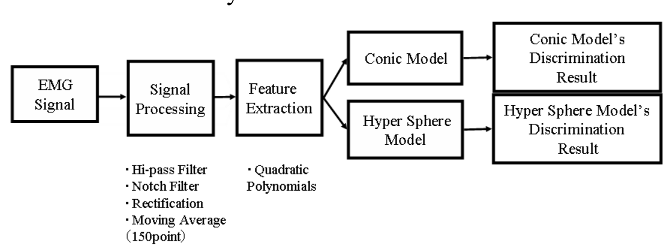

Fig. 1 Motion Discrimination

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A. Signal Processing

Figure 2 shows the low-pass filter (zero phase lag), and the summed EMG signals smoothed by using 100-, 150-, and 300- points moving averages. The summed EMG signals smoothed by the 100-point moving average are about 50 ms later than the low-pass filter, those smoothed by the 150-point moving average are about 75 ms later, and those smoothed by the 300-point moving average are about 150 ms. Moreover, the delay caused by the high-pass filter and the notch filter is about 20 ms. Thus, it is apparent that the smoothing causes a large delay.

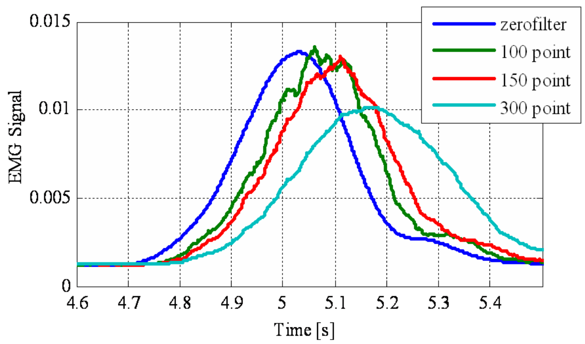
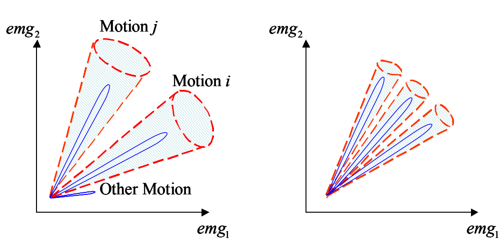


Fig. 2 Filtering Delay

B. Feature Extraction

Figure 3(a) shows an example of the decision regions for the conic models in feature space in the case of discriminating motions i and j. The shaded regions in the figure are the decision regions corresponding to these motions, the dashed lines are the boundaries of the decision regions, and the solid lines are the trajectories of the EMG signals when the motions are performed. The trajectories start from near the origin then return to this point because EMG signals are weak when the muscles don't contract and become strong when the muscles contract. The tops of the cones are the amplitudes of the EMG signals when the muscles don't contract and the cone-shaped decision region is located in such a way as to wrap around a trajectory corresponding to motions i, j. Because the trajectories corresponding to elbow motions are far from the trajectories of discriminated motions, the conic models prevent incorrect discriminations about elbow motions. However, as shown in Fig. 3(b), the decision regions become small for motions with similar trajectories. Because of this, quadratic polynomials are used to project the trajectories of motions into a feature space that has large enough decision regions.



(a) (b)

Fig. 3 Examples of Decision Regions using Conic Models

1) Quadratic Polynomials: The quadratic polynomials are used to extract a feature of each discriminated motion from the EMG signals. The feature corresponding to a motion takes on the biggest value when the motion is performed. The quadratic polynomials are used for every motion model.

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

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

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

2) Generation of Target Signal: A target signal is needed when determining the coefficients with the least squares method. The target signal ts_n is generated as follows. Each motion is performed once, and the sum S of the EMG signals of each channel is calculated. It is assumed that there are L channels of EMG signals and N motions are performed.

$$S = \sum_{l=1}^{L} emg_l \qquad (2)$$

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

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

where i ($i = 1, \cdots, n, \cdots, N$) is the number of peaks, d is a coefficient which takes a value of between 0 to 1, and e is the threshold value of S. The target signal is taken to be 0 while S is below e. It reaches a maximum when a corresponding motion is performed. Because the EMG signals can be measured and the teaching signals can be calculated in real time, coefficients can be updated without taking up any learning time.

C. Motion Discrimination

The location of the cone-shaped decision regions are determined by using 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. These signals are called motion signals. A conic model is composed for each motion. The discrimination result is the motion corresponding to the motion signal that has the largest positive value.

1) Conic Model: A motion signal using a conic model corresponding to motion i is expressed as follows:

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

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 the vertex angle of a cone. Note that $\mathbf{c}$ is the amplitude of the EMG signals when muscles don't contract, and $\mathbf{a}_i$ is the normalized amplitude of the EMG signals offset by $\mathbf{c}$ when EMG signals are at a peak as a result of performing motion i. $\mathbf{c}$ and $\mathbf{a}_i$ are obtained in real time.

The vertex angle ω_i can be determined from only the positional relation of trajectories corresponding to motions for discrimination. Figure 4 shows trajectories corresponding to motions i, j and k. First, we calculate the 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.

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

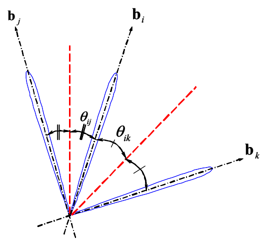


Fig. 4 Method for Obtaining the Vertex Angle of the Cone

2) Hyper-Sphere Model:

Figure 5 shows the decision regions created by the conic model and hyper-sphere model. The conic model (Fig. 5(a)) considers the motion trajectories to be linear, by smoothing EMG signals, and it is used to create decision regions. But, it might take time for a trajectory to enter a cone, as shown in the trajectory of motion 2 of Fig. 5(a), because the actual trajectories are nonlinear. This causes the discrimination processing time to increase. Then, we consider the creating of decision regions focused on the rising edge of the motion.

Figure 5(b) shows an example of the decision regions created by using the hyper-sphere model. The feature trajectory enters in the decision region quickly even if a complex feature trajectory is drawn ; this leads to a shorter discrimination processing time. Moreover, the hyper-sphere model can create decision regions that are more complex than the conic model by combining two or more decision regions of hyper spheres. In addition, the hyper-sphere model is thought to obtain a high discrimination accuracy even if there are fewer points included in the moving average. A motion signal corresponding to motion i is expressed as

$$msnew_i = \|\mathbf{feature} - \mathbf{s}\| sign\left\{\sum_{j=1}^{J} f(r_{ij} - \|\mathbf{feature} - \mathbf{c}_{ij}\|)\right\} \quad (6)$$

where $\mathbf{c}_{ij} = (c_{i1}, \cdots, c_{in}, \cdots, c_{iN})$ is the center vector of the hyper sphere, $\mathbf{r}_{ij}$ is the radius of the hyper sphere, $\mathbf{s} = (s_1, \cdots, s_n, \cdots, s_N)$ is the center vector of the first hyper sphere, and J is the number of hyper spheres.

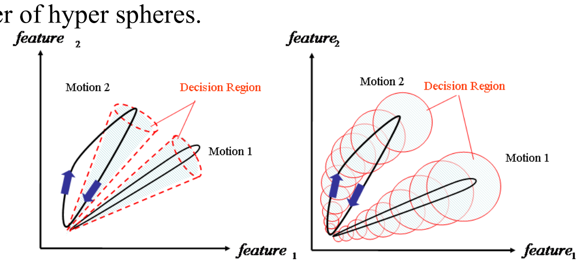


Fig. 5 Decision Regions

III. Experiment

A. Experimental Equipment

Figure 6 shows the experimental system. EMG amplifiers (EMG-025, Harada Hyper Precision Inc.) amplified 500 times (54 dB) were used to measure EMG signals. Disposable electrodes that were built into the preamplifier were employed. EMG signals were measured in four channels from the surface electrodes, and electrodes were arranged around the forearm. The PC (Pentium IV, 2.8 GHz, 1GB) served as the host computer. The 3D hand model control system was 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 were used for the DSP, A/D, and D/A conversions.

The EMG signals were full-wave rectified and smoothed with a 300 ms (conic model) or 150 ms (hyper-sphere model) moving average for feature extraction. The summing of the EMG signals had a threshold value. If the summed EMG signals fell below the threshold value, motions couldn't be discriminated.

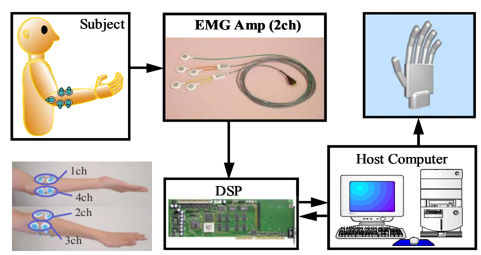


Fig. 6 Experimental System

B. Experimental Method

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

To obtain the learning parameters of the quadratic polynomials, we made the subjects perform each motion five times. To obtain the learning parameters of the conic models and hyper-sphere models, we made the subjects perform one motion each.

To verify the discrimination accuracies, we made the subjects perform motions 30 times each and found that the proposed method doesn't incorrectly discriminate hand motions as a result of elbow motions. Figure 7 shows the discrimination processing time decision method. Three times the standard deviation of the summed EMG signals in normal circumstances + the mean value is the start point of muscle activity, and the discrimination result of each motion is obtained at the end of the discrimination processing time [6].

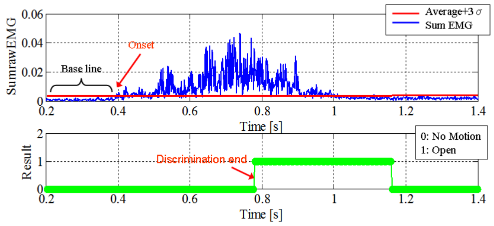


Fig. 7 EMG Onset

IV. RESULTS AND DISCUSSION

A. *Number of hyper spheres*

The hyper-sphere model has multiple decision regions, so it creates a complex decision region. Figure 8 shows the relationship between discrimination accuracy and the number of hyper spheres, and Fig. 9 shows the relationship between discrimination processing time and the number of hyper spheres. The discrimination accuracy was 90% or more for every subject when there were six or more hyper spheres. Moreover, the discrimination processing time stayed constant for every subject when there were ten or more hyper spheres. We compared the hyper-sphere model with the conic model under the assumption of ten hyper spheres.

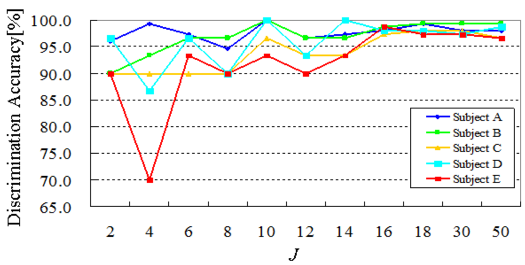


Fig. 8 Discrimination Accuracy vs. Number of Hyper Spheres

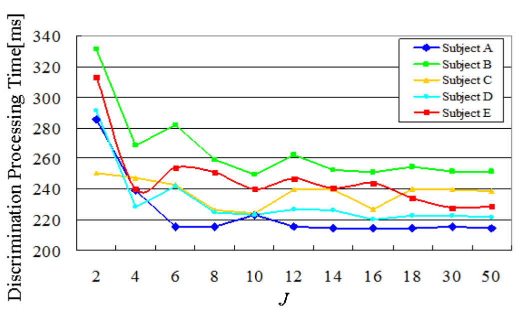


Fig. 9 Discrimination Processing Time vs. Number of Hyper Spheres

B. *Discrimination Accuracy and Discrimination Processing Time*

Discrimination accuracies of the conic model and hyper-sphere model were above 90 percent. Moreover, elbow motions did not interfere with the discrimination of the hand motion. Table 1 lists the discrimination processing times of the conic model, and Table 2 lists the discrimination processing times of the hyper-sphere model. The discrimination processing time was more than 300 ms for the conic model, but it was less than 300 ms for the hyper-sphere model, for every subject.

Table 1. Discrimination Processing Time of Conic Model

Subject	A	B	C	D	E	Average
Open	298.8	403.1	398.4	349.4	510.8	392.1
Close	370.4	387.5	280.8	238.7	472.8	350.0
Chuck	342.1	570.0	318.3	286.1	327.2	368.7
Wrist Ext.	371.9	345.4	384.4	479.2	271.8	370.5
Wrist Fle.	341.3	660.2	395.2	411.0	532.0	467.9
Average	344.9	473.2	355.4	352.9	422.9	389.9

Table 2. Discrimination Processing Time of Hyper-Sphere Model

Subject	A	B	C	D	E	Average
Open	184.2	280.5	260.6	250.4	288.4	252.8
Close	186.5	236.1	185.5	191.8	251.5	210.3
Chuck	293.2	217.8	215.8	206.0	160.1	218.6
Wrist Ext.	204.0	216.7	258.0	245.5	186.7	222.2
Wrist Fle.	253.0	296.1	202.3	223.2	315.0	257.9
Average	224.2	249.4	224.4	223.4	240.3	232.4

V. CONCLUSION

With the goal of discriminating motions of myoelectric limbs in real-time, we devised a real-time motion discrimination method for EMG signals that uses a hyper-sphere model. We reached the following conclusions after conducting a verification of the method.

1) The conic model and hyper-sphere model can discriminate open, grip, chuck, wrist extension, and wrist flexion motions with an accuracy above 90 percent and they help to eliminate incorrect discriminations that may be caused by elbow motions.
2) The discrimination processing time when using the hyper-sphere model was less than 300 ms.
3) We created a system for controlling a 3D hand model.

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REFERENCES

[1] M. Tsukamoto, T. Kondo and K. Ito, "A prosthetic hand control by nonstationary EMG at the beginning of motion," TECHNICAL REPORT OF IEICE, MBE2005-117, pp. 41-44, 2006, (in Japanese.)

[2] L. Ozyilmaz, T. Yildirim, and H. Seker, "EMG signal classification using conic section function neural networks," *Proc. of the 1999 International Joint Conference on Neural Networks*, Vol. 5, pp. 3601-3603, 1999.

[3] B. Karlık, M. O. Tokhi, and M. Alcı, "A fuzzy clustering neural network architecture for multifunction upper-limb prosthesis," *IEEE Transactions on Biomedical Engineering*, Vol. 50, No. 11, pp. 1255–1261, Nov. 2003.

[4] J. U. Chu, I. Moon, and M. S. Mun, "A real-time EMG pattern recognition system based on linear-nonlinear feature projection for a multifunction myoelectric hand," *IEEE Transactions on Biomedical Engineering*, Vol. 53, pp. 2232-2239, July 2006.

[5] N.Kurisu, N.Tsujiuchi, and T.Koizumi, "Prosthetic Hand Control using Motion Discrimination from EMG Signals", Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society(17820484.pdf), （2009）.

[6] Peter Konrad, "The ABC of EMG", Noraxon Inc. USA., pp. 60 .