# Motion Discrimination Technique by EMG Signals Using Hyper-Sphere Model

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*Abstract*— **This study developed a method of discriminating real-time motion from electromyogram (EMG) signals. We previously proposed a real-time motion discrimination method using hyper-sphere models that discriminated five motions (open, grasp, pinching, wrist extension, and wrist flexion) above 90% and quickly learned EMG signals. Our method prevents elbow motions from interfering with hand motion discrimination. However, we presume in our method that feature quantities do not change with time. Discrimination accuracy might deteriorate over time. Additionally, our method only discriminated three motions (open, grasp, pinching) for finger motions. This paper proposes the effectiveness of our method for changing feature quantities caused by time variation and a real-time motion discrimination method using new hyper-sphere models for four finger motions (open, grasp, pinching, and 2-5th finger flexion). We carried out two experiments and verified the effectiveness of our method for changing feature quantities and four finger motions discrimination using the new hyper-sphere models.**

## I. Introduction

Since hands and fingers shape most of our intellectual activities, they play various, critical roles in our daily lives. Many forearm amputees use prosthetic hands for many different purposes. Myoelectric prosthetic hands, which use electromyogram (EMG) signals in the persisting muscles as operation signals, are attracting attention because they resemble cosmetic prosthetic hands and can be naturally operated. Presently, the development of a motion discrimination method that can achieve intuitive operation and increase the number of discrimination motions is required to increase the level of effectiveness of the daily life of forearm amputees. Thus, methods have been studied that learn the relationships between patterns of EMG signals measured from muscles and classifier motions and estimate the motions that amputees want [1]-[4].

Many researchers have studied discrimination methods. Artificial neural networks have been used because they consider the nonlinearity of EMG signals, and the number of motions to be discriminated is increased. However, these methods take a long time to learn the EMG signals, and elbow motions interfere with their discriminated motions. In previous research, we devised a real-time motion discrimination method using hyper-sphere models that can learn EMG signals quickly. Moreover, the elbow motions did not interfere with the hand motions [5].

In this paper, we verify the effectiveness of our method for changing the feature quantities caused by time variation. Our method determines a feature space formed by feature extraction and classifiers (hyper-sphere models). The feature quantities change over time because the EMG signals change due to the time variations caused by fatigue, sweat, or electrode displacement, for example. We presume in our method that feature quantities do not change with time. However, discrimination accuracy might deteriorate over time because our method carries out motion discrimination using the parameters obtained by the initial learning for many hours. If myoelectric prosthetic hands are controlled by our method, errors might endanger the user. Many researchers have studied discrimination methods by considering time variation [6]-[9]. We also pursue a motion discrimination method by considering time variation. We carried out experiment and verified the effectiveness of our method for changing feature quantities.

Furthermore, this paper proposes a real-time motion discrimination method using new hyper-sphere models for four finger motions (open, grasp, pinching, and 2-5th finger flexion). In previous research, our method only discriminated three motions (open, grasp, pinching) for the finger motions. The number of tasks that can be done by the amputees is raised by increasing the number of discriminated finger motions. We carried out experiment and verified the effectiveness of our method using new hyper-sphere models for four finger motion discrimination.

## II. Motion Discrimination

Fig. 1 shows our motion discrimination system, which consists of the following parts: processing (high-pass filter, notch filter, rectification, and moving average), feature extraction (quadratic polynomials), and discriminators (hyper-sphere models). Quadratic polynomials are used to extract the features of the discriminated motions from the processed EMG signals to increase the discrimination accuracy. The hyper-sphere models discriminate finger motions using the extracted features.

Our method uses the size of the EMG signals measured from the channels. For example, Fig. 2 shows the trajectories of the EMG signals of two motions around the axis of the size

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of EMG signals measured from two channels. The trajectories start near the origin and return to this point because the EMG signals are weak when the muscles do not contract but strengthen when they do. Fig. 2 shows the decision region of the hyper-sphere models that are discriminators.

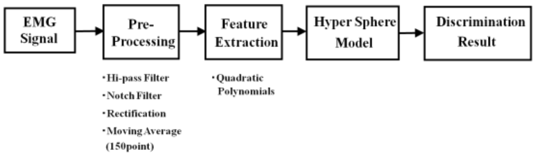


Figure 1. Motion Discrimination System

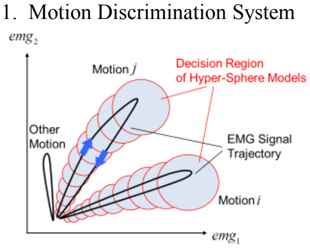


Figure 2. Decision Regions of Hyper-Sphere Models

## A. Feature Extraction

As shown in Fig. 3, since the decision regions become smaller for motions with similar trajectories around the axis of the size of EMG signals, it is difficult to use the EMG signals obtained by pre-processing. Therefore, quadratic polynomials are used to project the trajectories of the motions into a feature space that has large enough decision regions.

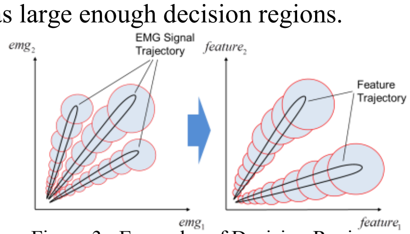


Figure 3. Examples of Decision Regions

*1) Quadratic Polynomials*: 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. Quadratic polynomials are used for every motion model.

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

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

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

*2) Generation of Teaching Signals:* A teaching signal is needed when determining the coefficients with the least squares method. Teaching signal $ts_n$ is generated as follows. Each motion is performed once, and sum $S$ of the EMG signals of each channel is calculated. We assume $L$ channels of EMG signals and $N$ motions are performed:

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

Since an 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 teaching 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, …, $n$, …, $N$) is the number of peaks, $d$ is a coefficient that takes a value between 0 to 1, and $e$ is the threshold value of $S$. The target signal is 0 when $S$ 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, the coefficients can be updated without using any learning time.

## B. Hyper-Sphere Model

Fig. 2 and Fig. 3 show the decision region of the hyper-sphere models that are discriminators. It is located in such a way as to wrap around a trajectory corresponding to motions $i$ and $j$. Because the trajectories that correspond to the elbow motions are far from the trajectories of the discriminated motions, the hyper-sphere models prevent incorrect discrimination of the elbow motions. The hyper-sphere models generate signals with a positive value when a certain motion for discrimination is performed and the feature trajectory (Fig. 3) enters the hyper-sphere for discriminating the motion and zero when other motions for discrimination and elbow motions are performed. These signals are called motion signals. Our method can discriminate many motions by studying the size of EMG signals in the multidimensional space. A hyper-sphere model is composed for each motion. A motion signal corresponding to motion $i$ is expressed as

$$msnew_i = \|\mathbf{feature}-\mathbf{s}\|\, sign\left\{ \sum_{j=1}^{J} f(r_{ij} - \|\mathbf{feature}-\mathbf{c}_{ij}\|) \right\} , \tag{4}$$

where $\mathbf{c}_{ij} = (c_i, \ldots, c_{in}, \ldots, c_{iN})$ is the center vector of the hyper sphere, $\mathbf{r}_{ij}$ is the radius of the hyper sphere, $\mathbf{s} = (s_1, \ldots, s_n, \ldots, s_N)$ is the center vector of the first hyper sphere, and $J$ is the number of hyper-spheres. The discrimination result is the motion that corresponds to the motion signal with the largest positive value.

## C. Real-Time Motion Discrimination using Hyper-Sphere Model

Fig. 2 and Fig. 3 show an example of the decision regions created using the hyper-sphere models, which can create complex decision regions by combining two or more decision regions of hyper spheres. Feature trajectory quickly enters the decision region even if a complex feature trajectory is drawn; this leads to shorter discrimination processing time. In addition, the hyper-sphere model obtains high discrimination accuracy even if the moving average includes fewer points. The discrimination processing time, which was less than 300 ms in our method, must be less than 300 ms to achieve real-time motion discrimination because the shortest delay time perceivable by users is roughly 300 ms, and a robot hand has a mechanical delay time.

## D. New Hyper-Sphere Models for Finger Motions

We created new hyper-sphere models for four finger motions to achieve real-time motion discrimination with high accuracy. We identified two features about the feature trajectory when subjects performed finger motions: 1) The feature trajectory at the start and the end of the performed motions was drawn in the same direction. 2) The feature trajectory is more complex around the maximum value of the muscle strength. The previous hyper-sphere models placed hyper spheres along the feature trajectory from the point where the muscles do not contract to the maximum value point at which they do. Thus, the new hyper-sphere models place hyper spheres along the feature trajectory from the point where the muscles do not contract to the maximum value point at which they do and from the maximum value point at which the muscles do to the point where the point where they do not contract (Fig. 4). Because of this, they can enclose the entire feature trajectory by hyper spheres and consider a more complex feature trajectory. We used this new model and experimentally verified the effectiveness of a real-time motion discrimination method for four finger motions.

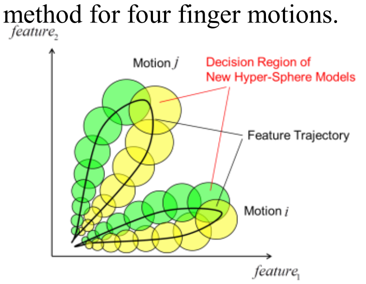

Figure 4. Decision Regions of New Hyper-Sphere Models

## III. Experiment

### A. Experimental Equipment

Fig. 5 shows our experimental system. We measured the EMG signals with EMG amplifiers (EMG-025, Harada Hyper Precision Inc.) that amplified the signals 500 times (54 dB). We employed disposable electrodes that were built into the preamplifier. EMG signals were measured in four channels from the surface electrodes that were arranged around the forearm. A PC (Core 2 Duo, 3.16 GHz, 2 GB) served as the host computer. A 3D hand model control system was designed using MATLAB/Simulink (dSPACE), and a 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 150- ms moving average for the feature extraction. The summing of the EMG signals had a threshold value. If the summed EMG signals fell below it, the motions couldn't be discriminated.

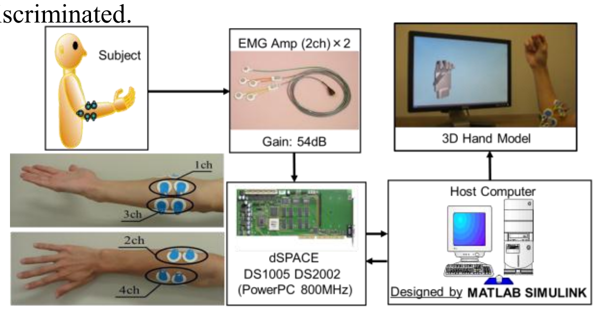

Figure 5. Experimental System

### B. Experimental Method

*1) Verification Experiment of Time Variation*: The subjects of the experiment were two able-bodied adults (Subjects A and B), who had previously participated in our experiments. The discrimination motions were three finger motions: open, grasp, pinching. The subjects performed three motions 20 times each to verify the discrimination accuracies. They did this six times in a row without resting their arms to verify the change in the discrimination accuracies and the discrimination processing time. We used the previous hyper-sphere models.

*2) Verification Experiment on Four Finger Motions*: Our experiment subjects were five able-bodied adults (A, B, C, D, and E). Subjects A and B are the same individuals from the verification experiment on time variation. Subjects C, D, and E did not participate in the previous experiments, so they spent one to two hours training how to use our experimental system. The discrimination motions were four finger motions (open, grasp, pinching, and 2-5th finger flexion). The subjects performed three motions 20 times each to verify the discrimination accuracies.

## IV. Results And Discussion

### A. Verification Experiment on Time Variation

The experiment ended after about one hour for every subject. Fig. 6 shows the discrimination accuracy. Our method could not discriminate with high accuracy the 5th and 6th experiments for Subject A and the 6th experiment for Subject B. Fig. 7 shows the discrimination processing time, which was less than 300 ms for every subject, every experiment, and every motion. Our method was effective compared with an experiment where the subjects performed three motions 20 times each four times in a row without resting their arms.

We thought why the 5th and 6th experiments for subject A and the 6th experiment for subject B resulted in less successful results. Our method treated the feature trajectories obtained from the size of the EMG signals in the multidimensional space to discriminate the motions. We found no big tendency in the change of the size of the EMG signals caused by the time variation. Thus, it is important to achieve a motion discrimination method that considers time variations to evaluate how time affects the feature trajectory. Fig. 8 shows the feature trajectories around the axis of the size of the feature quantity of the Subject A in the 6th experiment. The feature trajectories of each motion approached due to the time variations. The reason the feature trajectory was changed by the time variation is probably that the feature extraction parameter of the initial learning was insufficient to extract the features of each motion for the EMG signals after the time progress. The hyper-sphere models of the initial learning failed to discriminate the motions with high accuracy. We must feed-back the experimental data again to learn the parameters of the feature extractions or the hyper-sphere models. In the future, we will propose a new motion discrimination method to resolve this problem.

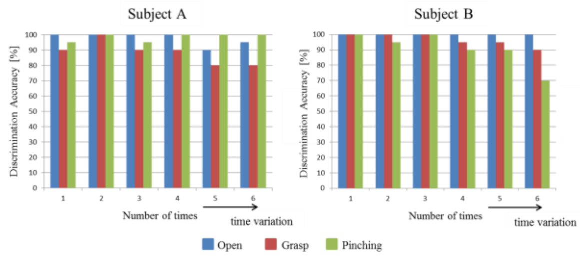

Figure 6. Discrimination Accuracy of Subjects A and B

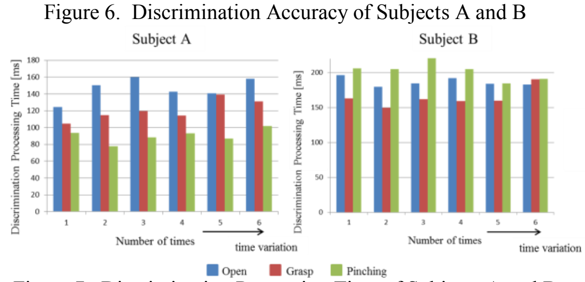

Figure 7. Discrimination Processing Time of Subjects A and B

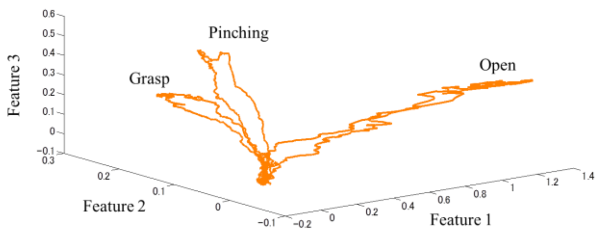

Figure 8. Example of Feature Trajectory after Time Variation

### B. *Verification Experiment on Four Finger Motions*

Table 1 lists the discrimination accuracy, which 90% for every subject and every motion. Moreover, the elbow motions did not interfere with the discrimination of the finger motions. Table 2 lists the discrimination processing time, which was less than 300 ms for every subject and every motion. Our new hyper-sphere models are effective against finger motion discrimination.

TABLE I. DISCRIMINATION ACCURACY OF NEW HYPER-SPHERE MODEL [%]

| **Discrimination Motions** | **Subject** | | | | | **Average** |
|---|---|---|---|---|---|---|
| | ***A*** | ***B*** | ***C*** | ***D*** | ***E*** | |
| Open | 95 | 100 | 100 | 100 | 100 | 99.0 |
| Grasp | 100 | 90 | 90 | 90 | 95 | 93.0 |
| Pinching | 95 | 100 | 100 | 100 | 100 | 99.0 |
| 2-5th Finger Fle. | 90 | 95 | 90 | 90 | 95 | 92.0 |
| Average | 95.0 | 95.0 | 95.0 | 95.0 | 97.5 | 95.8 |

TABLE II. DISCRIMINATION PROCESSING TIME OF NEW HYPER-SPHERE MODEL [ms]

| **Discrimination Motions** | **Subject** | | | | | **Average** |
|---|---|---|---|---|---|---|
| | ***A*** | ***B*** | ***C*** | ***D*** | ***E*** | |
| Open | 124.4 | 152.9 | 139.2 | 131.5 | 214.3 | 152.5 |
| Grasp | 99.3 | 116.1 | 121.6 | 199.0 | 232.2 | 153.6 |
| Pinching | 109.5 | 107.3 | 107.5 | 133.6 | 133.6 | 118.3 |
| 2-5th Finger Fle. | 87.2 | 91.6 | 71.2 | 146.3 | 134.6 | 106.2 |
| Average | 105.1 | 117.0 | 109.9 | 152.6 | 178.7 | 132.6 |

## V. CONCLUSION

We experimentally verified the effectiveness of our method that changes the feature quantities caused by time variation and a real-time motion discrimination method using new hyper-sphere models for four finger motions: open, grasp, pinching, and 2-5th finger flexion. We reached the following conclusions:

1) A method using hyper-sphere models was effective compared with an experiment where the subjects performed three motions 20 times each four times in a row.
2) Time variation does not negatively affect real-time motion discrimination in our method.
3) A method using new hyper-sphere models can discriminate four finger motions (open, grasp, pinching, and 2-5th finger flexion) with over 90% accuracy and helps eliminate incorrect discriminations that might be caused by elbow motions.


## ACKNOWLEDGMENT

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