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Self-Organized Clustering Approach for Motion Discrimination using EMG Signal

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***Abstract*— In order to control a myoelectric hand, it is necessary to discriminate among motions using electromyography (EMG) signals. One of the biggest problems in doing so is that EMG feature patterns of different motions overlap, and a classifier cannot discriminate clearly between them. Therefore, we propose a motion discrimination method to solve this problem. In this method, representative feature patterns are extracted from the EMG signals by using a self-organized clustering method, and user's intended motions are assigned as class labels to these feature patterns on the basis of the joint angles of the hand and fingers. The classifier learns using training data that consists of feature patterns and class labels, and then discriminates motions. In an experiment, we compared the discrimination rates of the proposed and conventional methods. The results indicate that the discrimination rate obtained with the former is 5–30% higher than that obtained with the latter; this result verifies the effectiveness of our method.**

I. Introduction

Recently, significant advancements have been made in robotics technology, and it has now become possible to control machines using bio-signals from the brain or muscles. One example of the application of this technology is the myoelectric hand; it can be used as a replacement for missing upper limbs of amputees and can perform many functions that are normally performed by the upper limbs. One of the difficulties in developing the myoelectric hand system lies in enabling the prosthesis to be controlled using EMG signals.

Generally, the myoelectric hand is controlled as follows. The estimation of a user's intended motion from EMG signals constitutes a type of pattern recognition problem. Fig. 1 shows a framework in which a user's intended motion is discriminated on the basis of EMG signals. There are two phases: a learning phase and a pattern recognition phase. In the pattern recognition phase, a classifier outputs myoelectric hand motions depending on control rules. The detailed process is as follows. The user performs a motion, and the $\mathbf{EMG}_t$ is measured at time t. This measured $\mathbf{EMG}_t$ is then used as the input signal to the classifier. A feature extraction function G_{FE} generates a feature vector $\mathbf{X}_t$ from the $\mathbf{EMG}_t$; $\mathbf{X}_t$ represents the characteristics of the intended motion. A

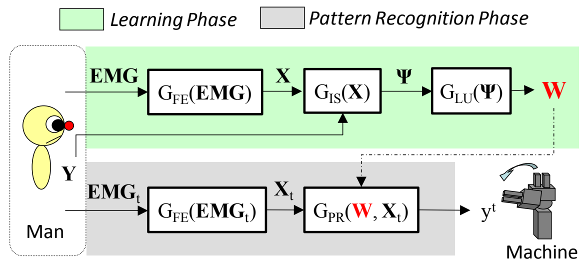

Fig. 1. Framework of motion discrimination using EMG signals.

recognition function G_{PR}, which has a classification function parameter $\mathbf{W}$, discriminates a motion y_k from input feature vector $\mathbf{X}_t$ and outputs the myoelectric hand motion. The parameter $\mathbf{W}$ determines the control rules for the classifier. These rules are updated using a training data set $\mathbf{\Psi}$ during the learning phase before users begin to discriminate motions. Training data consist of feature vectors and intended motions assigned as class labels. This training data is very important because it strongly affects the performance of the classifier.

In pattern recognition, the amplitude or frequency is typically used as the feature vector. With regard to motion discrimination, several classification functions have been proposed. These functions are divided into two types: (i) linear functions and (ii) nonlinear functions. The former include the AR model [1] and the linear discriminant function [2]. The latter include various artificial neural networks [3,4].

As mentioned previously, many classification methods have been proposed; however, only a few studies have attempted to address the issue of developing methods for the generation of training data. Conventional motion discrimination methods require users to take the initiative to generate training data. In these methods, users sequentially assign each particular motion to its corresponding feature vectors to generate the training data [5]. In other words, feature patterns extracted from the EMG signals during motion directly become a component of training data. In this study, we refer to this method as the conventional method. In general, the classifier is easily able to discriminate among motions provided that the training data consisting of different motions do not overlap with each other. However, users usually do not consider the overlap when generating the training data. Occupational therapists or experts may advise users when generating training data; nevertheless, it is difficult to judge which training data is suitable for the classifier when the number of motions is large. As a result, the classifier is sometimes unable to effectively discriminate among different motions.

In this study, we propose a method to discriminate motions

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clearly from EMG signals. The challenge is to generate training data that would enable the classifier to easily discriminate among different motions. In our proposed method, we employ a self-organized method to generate representative feature patterns from all feature patterns of EMG signals measured during several motions; these representative feature patterns form the components of the training data. Subsequently, the user's intended motions are assigned as a class label to each feature vector by using the joint angles of the hand and fingers.

We verify the effectiveness of our proposed method by discriminating among some motions using both the proposed and conventional methods. We then compare the discrimination rate of both methods.

II. Self-Organized Clustering Method for Motion Discrimination

In our proposed method for discriminating motion, we generate training data that enables the classifier to easily discriminate motion, and then reveal this training data to the users. Motion discrimination is considered to be successful if the feature patterns of users match those of the training data during the discrimination process. Therefore, users train themselves to match their patterns to the feature patterns contained in the training data.

Our method is divided into the following two processes.

A) Generation of representative feature patterns from EMG signals using self-organized clustering.

B) Assignment of user's intended motion as a class label to each representative feature pattern by using joint angles of the hand and fingers.

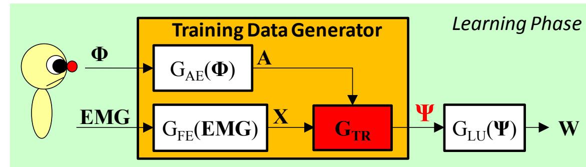
An overview of the processes is showed in Fig. 2, and their details are explained below.

A. Generation of representative feature patterns using self-organized clustering

In the learning phase, we generate representative feature patterns from EMG signals using self-organized clustering. Users perform some motions such as grasp and open (shown in Fig. 4) that they intend to realize with the myoelectric hand. EMG signals are detected on the surface of the user's skin and the joint angles of the user's hand and fingers are measured during the motions. The feature extract function G_{FE} (Fig. 2) receives **EMG**, which is the vector representing EMG signals of all motions, and generates the feature vector $\mathbf{x}_i$. $\mathbf{X}$ is the set of $\mathbf{x}_i$, where

$$\mathbf{X} = \{\mathbf{x}_i \mid \mathbf{x}_i \in \Re^D, i = 1,2,\cdots,n\} \tag{1}$$

Here, n is the number of feature vectors that have been extracted. In this study, the amplitude and frequency of the EMG signals are selected as feature vectors. We employ the short-time Fourier transform and use the resultant spectrum of 20–400 Hz. The power spectrum **F** is smoothed with *Ip* widths to acquire the rough features of the spectrum. The



Φ: Joint angles **EMG**: Electromyogram **A**: Joint angle vector
X: Feature vector **Ψ**: Training data **W**: Parameter of discrimination function

Fig. 2. Overview of the generation of training data using self-organized clustering in the learning phase.

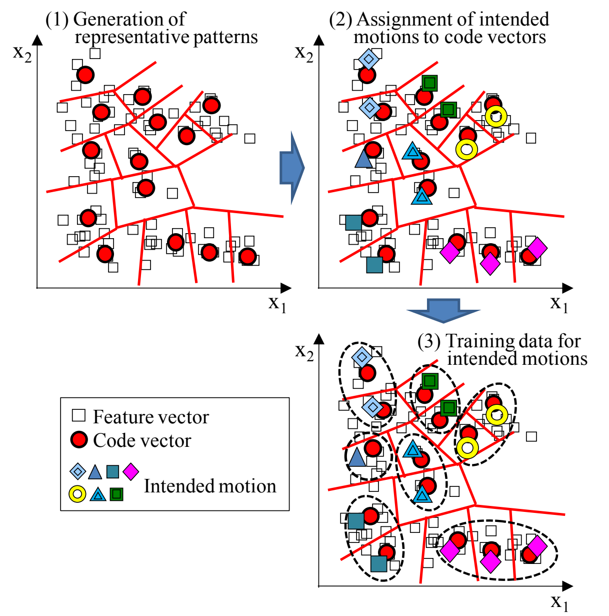


Fig. 3. Process of generating training data (two-dimensional conceptual diagram).

smoothed spectrum is divided into N ranges, and the spectrum of 20+(380/N)*i Hz (i = 1,…,N) is extracted to yield feature vectors. The feature extract function of joint angles G_{FA} (Fig. 2) generates a joint angle vector **A** from the joint angles **Φ**.

$$\mathbf{A} = \{\mathbf{a}_i \mid \mathbf{a}_i \in \Re^D, i = 1,2,\cdots,n\} \tag{2}$$

A is added to **X**; thus, each $\mathbf{x}_i$ contains the angle information.

Fig. 3 shows the process used to generate training data (Fig. 2, G_{TR}). In G_{TR}, representative feature patterns are generated from **X** by using a vector quantization method that is a type of self-organized clustering (Fig. 3, (1)). In this method, the space of **X** is divided into subspaces, and a code vector is arranged in each subspace. This is similar to the Voronoi diagram, and each code vector represents a unique subspace [6]. We consider the code vector set **Ξ** as containing the representative feature patterns; these patterns are generated in the following manner.

The code vectors ξ_j (j = 1,2,3) are located randomly in the space of the feature vector set **X**. We calculate the distance from $\mathbf{x}_i$ (i = 0) to ξ_j (j = 1,2,3), and the position of the nearest ξ_j is updated by (3) as it approaches $\mathbf{x}_i$ (i = 0).

$$\xi_j = \xi_j + \alpha \cdot (\mathbf{x}_i - \xi_j) \tag{3}$$

Here, α is the learning coefficient. We carry out the same process for every $\mathbf{x}_i$ (i = 1,…,n) and update the position of ξ_j.

Next, a new code vector is added to the space of $\mathbf{X}$, and ξ_j is updated in the same manner. These steps are repeated until the number of code vectors required by the setup condition is satisfied.

We add angle information to these resultant code vectors using the joint angle vector $\mathbf{A}$. The angle information is used to assign a user's intended motion to each code vector in the next step. The average joint angle of the nearest k feature vectors $\boldsymbol{\delta}_i$ ($i = 1,\ldots,k$) is set as the angle information of the code vector ξ_i.

B. Assignment of user's intended motion to representative feature patterns using joint angles of the hand and fingers

The code vector set $\boldsymbol{\Xi}$ is a candidate for obtaining training data. In the process described in this section, we assign the user's intended motion to individual code vectors on the basis of joint angles to generate training data. Joint angles are considered to be closely related to human motion, and therefore, they can be used as indicators of a user's intended motion. Therefore, a user can easily adapt their EMG patterns to those of the training data.

First, users perform some motions that they intend to realize with the myoelectric hand. They maintain their hand or finger posture for a few seconds, during which the joint angles of their hand and fingers are measured. These motions are called standard motions and the joint angle set $\boldsymbol{\Theta}$ is used as criteria.

$$\boldsymbol{\Theta} \equiv \left\{ \boldsymbol{\theta}_{y_1}, \boldsymbol{\theta}_{y_2}, \cdots, \boldsymbol{\theta}_{y_k}, \cdots, \boldsymbol{\theta}_{y_M} \right\} \tag{4}$$

$\boldsymbol{\theta}$ is the joint angle vector of one motion, y_k is the type of motion, and M is the maximum number of motions. Next, we calculate the Euclidian distance of joint angles between each component of $\boldsymbol{\Theta}$ and $\boldsymbol{\Xi}$, and the standard motion with the minimum distance is considered as a suitable candidate for the assigned motion. Here, we must determine the maximum permitted distance. If the feature vectors that are situated at a considerable distance from the standard motion are employed as training data, there is a high possibility that the feature vectors of different motions will be similar. Therefore, we set a threshold ε, and only when the distance is less than this threshold, the standard motion is assigned to the code vector as the user's intended motion. Feature vectors with values greater than ε are rejected. A pair of data elements consisting of a code vector as a feature vector and a user's intended motion as a class label constitutes the training data. In addition, the optimum value of ε is different for different individuals; therefore, ε is uniquely set for each subject on the basis of the result of the preliminary experiment.

The learning function G_{LU} (Fig. 2) calculates the parameter $\mathbf{W}$ of the pattern recognition function from the training data set. In the pattern recognition phase, we employ a three-layer feed-forward neural network (ANN) for the purpose of classification. In the same manner as that shown in Fig. 1, the parameter $\mathbf{W}$ is transmitted to the pattern recognition phase, and users are then able to discriminate motions.

Training data is generated by self-organized clustering; therefore, users are unaware of the type of feature pattern assigned to each motion in the training data. To solve this problem, we visually display the feature patterns to users, who can then train themselves to match their EMG patterns to those of the training data.

III. Experiment

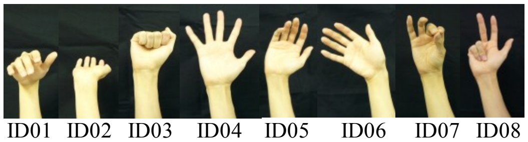
In order to verify the effectiveness of the proposed method, we carried out the following experiments. We compared the discrimination rate obtained by using the proposed method to that obtained by using the conventional method.

A. Experimental Setup

In the experiments, subjects discriminated eight forearm motions using both the conventional and the proposed methods. One healthy female (Subject A) and three healthy males (Subject B, D, and E), all in their twenties, participated as subjects. The target motions are the eight forearm motions shown in Fig. 4. The wrist motions are flexion, extension, radial flexion, and ulnar flexion. The hand motions are grasp, open, pinching, and 4-5th finger flexion. EMG signals are measured on three different muscles of the left forearm during the motions. The area of the amputation stump is narrow; hence, it is not possible to place many sensors on it. Therefore, we try to discriminate many motions by using a minimum number of sensors. In this experiment, we set EMG sensors to the flexor carpi ulnaris muscle, extensor carpi ulnaris muscle, and flexor pollicis longus muscle (Fig. 5). These muscles are used during the target motions. The sampling rate is 1600 Hz. The total dimensionality of the feature vector is 51, 1 amplitude and 16 spectrums in each sensor. We use a data glove (Immersion Corp, Cyber Glove) to measure 18 joint angles of the hand and fingers, and the sampling rate is 50 Hz.

Initially, the subjects discriminated motions using the conventional method. They sequentially taught motions to the classifier using a keyboard. The combinations of motion labels and feature vectors extracted during the motion formed the training data. Then, the motion discrimination tests were carried out. In each trial, the subjects maintained a posture of a particular motion for 3 s. Approximately 150 feature extractions were carried out. We performed the discrimination tests online; hence, this value is different for different trials. The number of correct discriminations divided by the total number of discriminations gives the discrimination rate. The subjects carried out three trials for each motion, and the average discrimination rate of the three trials was calculated.

Then, the subjects generated training data using the proposed method. The training data were presented to the subjects and they trained themselves to match their feature patterns to those of the training data. A training period of 15 min and a motion discrimination test consisting of three trials for each motion constituted one set; subjects carried out four sets of tests. The parameters of the ANN are as follows. The number of hidden layers was 55; number of output layers, 8; and the learning rate, 0.05. Learning continued until the error fell below 0.01 or for 30000 learning steps.



01: Flexion 02: Extension 03: Grasp 04: Open
05: Radial flex. 06: Ulnar flex. 07: Pinching
08: 4-5th finger flex.

Fig. 4. Subject's eight forearm motions for discrimination.

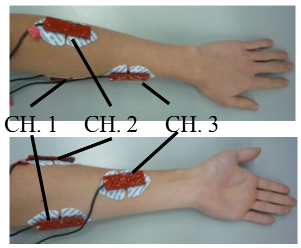


Fig. 5. Positions of surface electrodes.

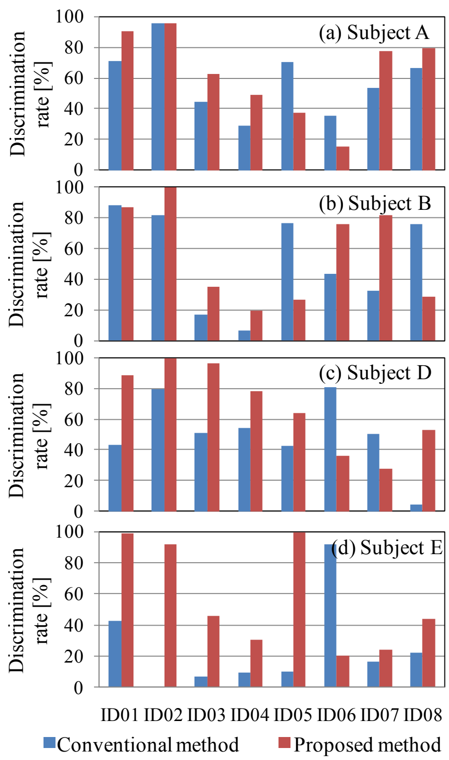


Fig. 6. Difference between discrimination rates of the proposed and the conventional methods.

Table 1. Subject's eight forearm motions for discrimination.

	Average discrimination rate [%]	
Subject	Conventional method	Proposed method
A	58.60	63.84
B	52.67	56.79
D	51.07	68.21
E	24.97	56.88

B. Experimental Result

We compared the differences in the discrimination rates obtained by the proposed and conventional methods. Fig. 6 shows the average discrimination rate for each motion of each subject. The result of the conventional method is the average value of three trials, whereas that of the proposed method is the highest rate obtained among the four sets for each subject.

As can be seen from these graphs, the discrimination rate for six motions for Subject A, B, and D and seven motions for Subject E is higher with the proposed method than with the conventional method. Therefore, the proposed method can be considered as effective for motion discrimination. We calculated the average discrimination rate for all eight motions (Table 1). The average discrimination rate of the proposed method was 5–30% higher than that of the conventional method in the case of all subjects. Subject E, in particular, was not familiar with motion discrimination using EMG signals, unlike the other subjects; however, even he was able to discriminate motions better using the proposed method. Nevertheless, the discrimination rate in his case was still lower than that of other skilled subjects. In this experiment, the training time was approximately 1 h, and thus, an unskilled user like Subject E is considered to require more training to effectively carry out motion discrimination.

IV. Conclusion

In this paper, we have proposed a method to discriminate motions stable from EMG signals by using self-organized clustering. In this method, we generate representative feature patterns from EMG signals and then assign user's intended motions as class labels to each representative feature pattern; these constitute the training data. In an experiment to verify the effectiveness of our method, we compared the discrimination rate of the proposed and conventional methods. The discrimination rate of the former was 5–30% higher than that of the latter, and we verified that the former was effective for motion discrimination. The amplitude and frequency of EMG signals were employed as feature vectors in this research. However, the type of feature vector used for motion discrimination is important; therefore, we need to investigate the effectiveness of the proposed method using different types of feature vectors.

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