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The evaluation of the discriminant ability of multiclass SVM in a study of hand motion recognition by using SEMG*

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Abstract— **Electromyogram (EMG) is a kind of biological signal that is generated because of excitement of muscle according to the motor instruction from a brain. We have been experimentally developing the hand motion recognition system by using 4 channels forearm EMG signals. In our system, in order to classify measured EMG SVM (Support Vector Machine) that has higher discriminability is used. Often SVM is used as a non-linear classifier. But, In the conventional system that we developed, we used a canonical discriminant analysis (CDA) method. CDA method is linear discriminant function, but it has shown good experimental results. Therefore, we have compared the discriminant ability between SVM and CDA. In this report, we will describe about the results of this experiment.**

I. INTRODUCTION

An Electromyogram (EMG) is measured as the electrical signal associated with the activation of the muscle. EMG can be used for a lot of studies (e.g., Clinical, Biomedical, Basic Physiological, Classical Neurological, and Biomechanical studies). Recently, in order to describe the neuromuscular activation of muscles within functional movements, kinesiological electromyography deserves attention and is established as an evaluation tool for various applied research.

In order to apply it simply, the surface EMG (SEMG) which is measured from the skins surface, is widely used as a control source for human interface such as myoelectric prosthetic hands[1-2]. The SEMG related system has many practical examples of applications in various fields such as human interfaces. Human interfaces are reported by many researchers, and we call them "SEMG interfaces". Our study also aims to develop the SEMG interfaces like myoelectric prosthetic hands. Actually, we use a 96-channel matrix-type surface electrode attached to the forearm. SEMG measured from these electrodes are analyzed and a hand movement corresponding to the SEMG pattern is recognized in our system. In the hand movement recognition, not all electrodes are used. Reduced electrode sets (from 4 to 16 channels) are selected using the Monte Carlo method[3].

About a SEMG interface, it is desirable to operate it with the same feeling as the sensations of real body movement. In order to achieve this objective, accuracy recognition of motion is one of important factors. However, conventional SEMG interfaces have mainly focused on how to achieve the accuracy using sophisticated signal-processing techniques which are represented by a neural network model and a nonlinear one. In recent years, Non-Linear Support Vector Machine (SVM) has been attracting attention as a new signal processing technique. This technique has been reported to correspond to a variety of pattern recognition problem. In the conventional system that we developed, we used a canonical discriminant analysis (CDA) method. Although CDA is a linear discriminant method, good experimental results have been obtained by using CDA[4]. Therefore, In case of the pattern recognition problems using SEMG, we thought that there is no need to use non-linear discriminant function.

SVM is usually used as a non-linear discriminant function. And it is said that the non-linear SVM is good to solve the pattern recognition problem. However, SVM is also constructed as a linear discriminant function. In this study, in order to evaluate performance and usefulness of SVM as a linear discriminant function, SVM was constructed as a linear system. And recognition rate of this linear SVM was compared with non-linear SVM and CDA. As mentioned earlier, in our hand movement recognition system, the number and the position of using electrodes are selected using the Monte Carlo method. In this study, the change of the recognition rate for the change of the number of the electrodes are also investigated by using linear and non-linear SVM as a discriminant function.

II. SYSTEM DESIGNS

A block diagram of our SEMG system is shown in Fig.1. As shown in this figure, the system consists of a 96-channel surface electrode, a SEMG amplifier, and a personal computer that is used for analyzing SEMG. The multi-electrode is attached to the forearm, and SEMGs from the forearm are amplified and filtered in the SEMG amplifier. And then amplified signals are analog to digital converted and analyzed in a personal computer.

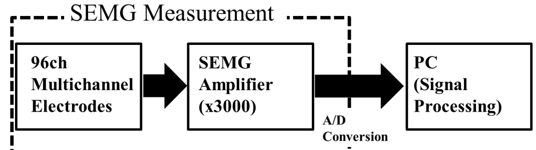

Fig. 1. A block diagram of our system

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A. 96ch Multi-electrode and SEMG measurement system

The multi-electrode is one of the features and the key of our system. Fig.2 shows a multi-electrode. This is used in order to detect an individual difference of a measuring SEMG while it is being used by the subject moving their hand. This multi-electrode is attached to the forearm. The detail of a 96 channel electrode is also shown in Fig.3. As shown in this figure, this multi-electrode is composed of 96 silver electrodes (6x16). Each electrode is 1mm in diameter and that is arranged with an electrode interval, 10mm long and 16mm wide. To fit a bodyline with this electrode, we use a flexible silicone rubber as the base of 96 silver electrodes.

And we also designed the SEMG amplifier, which amplifies an SEMG signal about 3,000 times and the frequency band is limited from 10 Hz to 1,000 Hz. The amplified SEMG signals are sampled by a 16-bit A/D converter at a rate of 2,000 Hz.

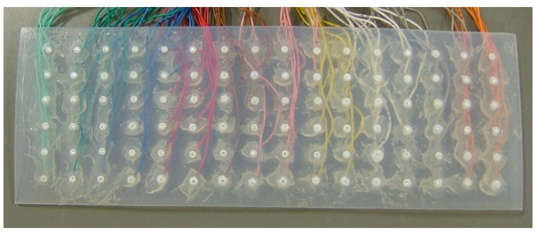


Fig. 2. A Picture of 96ch Multi-Channel Electrode

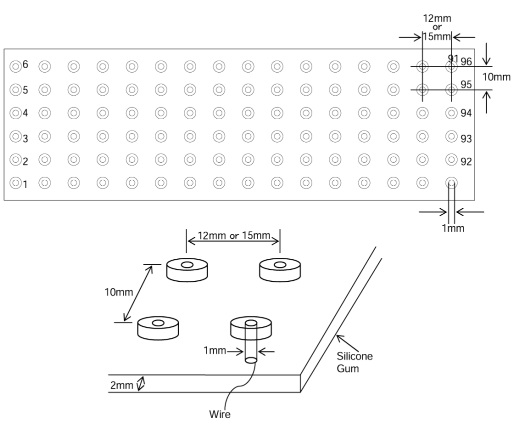


Fig. 3. The Detail of 96ch Multi-Channel Electrode

B. Support Vector Machine (SVM)

In this study, we are using Support Vector Machine (SVM) as a classifier. An original SVM is a linear classifier, but SVM can be extended to non-linear perceptron type classifier without losing convenience of the learning by using a kernel function. In SVM, in order to separate the characteristic vector of an unknown pattern X in two classes, the discriminant function as shown in equation (1) is created by using training data.

$$f(x) = sign(\sum_{i=1}^{d} \lambda_i y_i K(x_i, x) + b) \tag{1}$$

In this equation, y_i is the class label that corresponds to the learning of the i place sample xi, λ_i is the Lagrange multiplier, b is the bias term. $K(x_i, x)$ is a kernel function. A kernel function map a linearly inseparable larning data to high-dimensional featur space, and then this data become a linearly separable in the high-dimensional space. A SVM without kernel function is a linear classifier. In our experiment, the Radial Basis Function kernel is used. This kernel is shown in equation (2).

$$K(x_i, x) = exp(-\gamma||x_i - x||^2) \tag{2}$$

To find the discriminant function shown in equation (1), it is necessary to botain λ_i that maximizes the following objective function (3).

$$Objective\ func.: \sum_{i=1}^{d} \lambda_i - \frac{1}{2}\sum_{i=1}^{d} \lambda_i \lambda_j y_i y_j K(x_i, x) \tag{3}$$

$$Subject\ to: \sum_{i=1}^{d} \lambda_i y_i = 0, 0 \leqq \lambda_i \leqq C \tag{4}$$

Tolerable recognition error is determined by C. The kernel parameters must be determined in advance at the time of learning, its value comes heavily involved in the recognition rate.

In this study, suitable kernel parameters are determined by using Particle Swarm Optimization method (PSO). PSO is a method that can be used to find approximate solutions to difficult numeric maximization and minimization problems. Parameter estimation procedure using the PSO will be as shown in the following Fig.4.

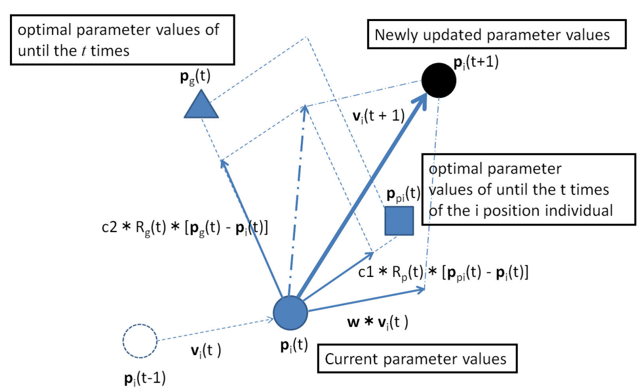


Fig. 4. The Description Of PSO method

Originally SVM is a technique to solve binary classification problems. To extend SVM to multi-class problems, the one against one method is a suitable mehtod for practical use. The one against one method uses $N(N+1)/2$ discliminant functions for N-class problems. In our study, 18 types of hand movements have to be recognized. Therefore, 171 discriminant functions are necessary. All programs are written in the C language and SVM multiclass libraries are also used.

III. EXPERIMENT AND RESULTS

Five normal subjects were tested for our objective. In this experiment, the SEMG feature extraction was the integrated value of the SEMG amplitude during 300 ms. Equation (5) shows the feature extraction X_i.

$$X_i = C \sum_{n=1}^{N} |x_i(n\Delta t)| \tag{5}$$

Where $x_i(t)$ is the SEMG signal value of i channel at time t and Δt is sampling period. C is the constant used to normalize patterns, and $T = N\Delta t$ is integration period. As mentioned earlier, T was fixed to 300 ms in the experiment.

In this experiment, we measured data set of SEMG every each hand movement five times. One data set of SEMG was composed of 96 channels SEMG data that was measured during 900 ms. Next, learning data and classification data were generated from measured data set. SEMG data that was measured during 900 ms was divided into 10 segments for every 300 ms that is the length of integrated time as a feature extraction, and the start point is shifted every 60 ms as shown Fig.5. First segment of this segments was set as a learning data, and all 10 segments were used as classification data.

Using these data, suitable parameters of linear and non-linear (using RBF kernel) SVM were estimated by PSO. And then, the experiments of hand movement recognition were carried out for classification data by using SVMs that learning were completed. As mentioned earlier the used set of SEMG electrodes was determined by the Monte Carlo method[3]. In these experiments, following 18 movements that contain movement of fingers are tried to recognize. Tested movements were 1.Wrist Flection, 2.Wrist Extension, 3.Grasp, 4.Release, 5.Radial Flection, 6.Supination, 7.Pronation, 8.Supination, and ten movements of fingers and thumb.

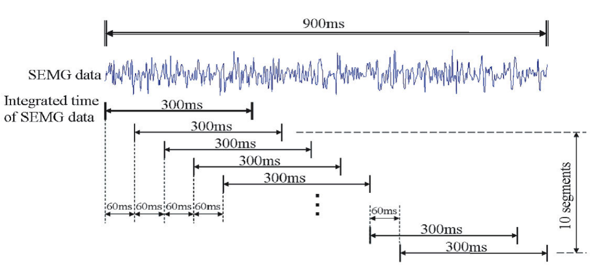


Fig. 5. A schematic view of the SEMG segmentation

The results of experiments are shown from Table I to Table III. These results indicate the relationship between the number of electrodes and averaging recognition rate for 3 subjects (subject A, subject B, and subject C). Table I(a), Table II(a), and Table III(a) show the results by using the linear SVM, and Table I(b), Table II(b), and Table III(b) show the results by using the non-linear SVM for each subject. As shown in these tables, in case of little number of electrodes (the number of electrode ≤ 3), the recognition rate of non-linear SVM is higher than the recognition rate of linear SVM. When the number of electrodes more than 4, recognition rate of linear SVM is higher than non-linear SVM in all subjects.

In the case that the number of electrodes less than 4, it seems that non-linear SVM is better than linear SVM. However, recognition rates are smaller than 90% in all cases. We think that 3 electrodes are too little number for sufficient recognition rate in all cases. And in the case that the number of electrodes more than 4, about the same recognition rate of sufficient height is obtained by linear and non-linear SVM. Non linear SVM is more complicated than linear SVM, and calculation time of non-linear SVM is longer than the time of linear SVM. From these results, we think that linear SVM is suitable to use it for the hand movement recongition.

TABLE I

THE RELATIONSHIP BETWEEN THE NUMBER OF ELECTRODES AND RECOGNITION RATE OF THE SUBJECT A

(a) using Linear SVM

Number of Electrodes	C parameter	Recog. Rate[%]
1ch	1.005217017	5.56
2ch	162.9115409	43.33
3ch	10.4209074	87.22
4ch	248.2563827	94.56
5ch	22.3080422	99.56
6ch	643.6796284	98.67

(b) using Non-Linear SVM

Number of Electrodes	C parameter	Gamma Parameter	Recog. Rate[%]
1ch	0.501302731	1.614070954	44.00
2ch	0.038660765	0.02296308	82.89
3ch	0.029306185	0.003345731	90.00
4ch	0.01521869	0.001631888	93.33
5ch	0.028592132	0.000701303	94.56
6ch	0.103502463	0.000433237	94.44

TABLE II

THE RELATIONSHIP BETWEEN THE NUMBER OF ELECTRODES AND RECOGNITION RATE OF THE SUBJECT B

(a) using Linear SVM

Number of Electrodes	C parameter	Recog. Rate[%]
1ch	1.005217017	5.56
2ch	1.005217017	37.00
3ch	165.721503	77.44
4ch	3.264350566	89.78
5ch	16.67244749	96.33
6ch	4568.985029	95.89

(b) using Non-Linear SVM

Number of Electrodes	C parameter	Gamma Parameter	Recog. Rate[%]
1ch	0.000289103	0.000385206	30.78
2ch	0.0026195	0.001092593	53.56
3ch	0.004748287	0.00012165	79.78
4ch	0.859155991	0.001036606	88.44
5ch	0.090471675	0.000159232	90.00
6ch	0.038983623	0.000062951	88.56

TABLE III

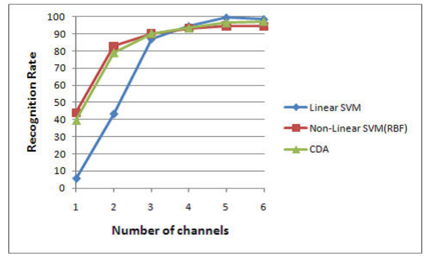
THE RELATIONSHIP BETWEEN THE NUMBER OF ELECTRODES AND RECOGNITION RATE OF THE SUBJECT C

(a) using Linear SVM

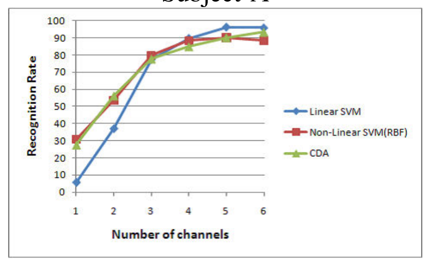
Number of Electrodes	C parameter	Recog. Rate[%]
1ch	1.002325781	5.56
2ch	2.234249033	38.00
3ch	7.357165269	74.89
4ch	4.944682884	89.00
5ch	4725432.668	94.44
6ch	127709711.9	95.33

(b) using Non-Linear SVM

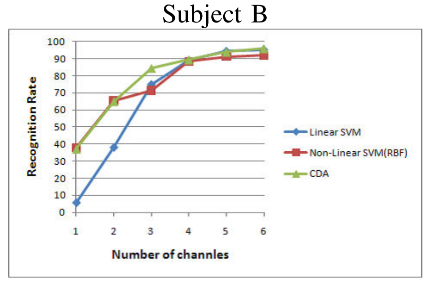
Number of Electrodes	C parameter	Gamma Parameter	Recog. Rate[%]
1ch	1.419527699	1.965272	37.78
2ch	0.035879983	0.018585702	65.56
3ch	0.023665726	0.00012165	71.44
4ch	0.000264457	0.000584923	88.44
5ch	0.004846967	0.00211603	91.22
6ch	0.22310442	0.00109642	91.89



Subject A



Subject B



Subject C

Fig. 6. The relationship between recognition rate and the number of electrodes

From Fig.6 shows the relationship between the recognition rate and the number of electrodes when non-linear SVM, linear SVM and CDA were used each. As shown in these figure, Though the structure of CDA is simple, good recognition rate was obtained using CDA. In the case of small number of the electrodes, recognition rate using CDA is about the same as using non-linear SVM. From these results, if the position of electrodes are selected suitably, CDA and linear SVM shows sufficient ability in recognition rate.

IV. CONCLUSIONS

There are a lot of researches of recognizing hand movements by using SEMG. Many of them use a fixed positions of SEMG electrodes and a non-linear discriminant function to identify hand movement. In our hand motion recognition system, suitable positions of electrodes are decided by the Monte Carlo method [3] and Canonical Discriminant Analysis that is one of linear discriminant functions is used. Our method establishes enough high recognition rate [4]. However, we would like to investigate the change of recognition rate in case of using other discriminant functions. So, in this study, linear and non-linear SVM were constructed and used in our hand movements recognition system as discriminant functions.

Non-linear SVM is a popular discriminant function in the BCI, and this function establish high recognition rate in many cases. However, as mentioned earlier, the recognition rate using non-linear SVM was about the same as using CDA in our system. We think that non-linear discriminant functions are useful for complicated systems like as BCI, and even the linear discriminant function is useful for simple system like as our recognition system. In this study, we used the Radial Basis Function (RBF) as a kernel for non-linear SVM. However, there are many kind of non-linear kernel for SVM. In order to establish higher recognition rate, we have to study about other kernels in future.

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