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Monte Carlo method for evaluating the effect of surface EMG measurement placement on motion recognition accuracy

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***Abstract*— Surface electromyogram (SEMG) is one of the most important biological signal in which the human motion intention is directly reflected. Many systems use SEMG as a source of a control signal. (We call them "SEMG system"). In order to develop SEMG system, constructions of discriminant function and SEMG measurement placement are important factors for accurate recognition. But standard criterions for selection of discriminant function and SEMG measurement placement have not been clearly defined. Almost all of the conventional SEMG system has decided to select measurement placements of SEMG according to standard general anatomical structure of the human body and that mainly focused on signal processing method. However, SEMG measurement placement is also critical for recognition accuracy and evaluating the effect of SEMG measurement placement is important.**

In this study, we investigate the effect of SEMG measurement placement in hand motion recognition accuracy. We use a 96-channels matrix-type surface multielectrode and four channels are selected as the SEMG measurement placements from the channels that compose multielectrode. 5,000 configurations of SEMG measurement placements are generated by randomly selected number and each configuration is assessed by motion recognition accuracy (i.e. Monte Carlo method). In order to consider the influence of discriminant analysis, our system employs the linear discriminant analysis and nonlinear discriminant analysis. Each selected SEMG measurement placement is evaluated by those two types of discriminant analysis and the results are compared with each other. The experimental results show that motion recognition accuracy differs between these two analyses even if the same SEMG measurement placement is used. Not all optimal measurement placements for linear discriminant function suit for nonlinear discriminant function. The outcome of these investigations, the SEMG measurement placement should be taken into consideration and it suggests the necessity of evaluating the optimal measurement placement depending on a discernment analysis..

I. INTRODUCTION

TODAY, surface electromyogram (SEMG) that measured from skin surface is widely used as a control signal for many devices. Because, SEMG is one of the most important biological signal in which the human motion intention is directly reflected. And various devices using SEMG are reported by lots of researchers. Those devices which use SEMG as a control signal, we call them "SEMG system". There are many example of application in various fields. For example, prosthetic manipulators, assists system for the disable , and many applied examples [1-7].

In SEMG system, to achieve high accuracy recognition is an important requirement. However, individual differences of SEMG cause difficulty in the accurate recognition of motions. In order to correctly decipher the intended motion, SEMG system needs to solve the factor of individual differences of SEMG. There are two important and effective factors to settle individual differences. The first one is SEMG measurement placement. It means the selection of measurement position which can acquire effective information about motions. The second is signal processing method. It means how to construct a statistical discrimination method. As for these two factors, standard criterions for selection of discriminant function and SEMG measurement placement have not been clearly defined. Almost all of the conventional SEMG system has decided to select measurement placements of SEMG according to standard general anatomical structure of the human body and that mainly focused on signal processing method. Examples of these methods are Neural Network, Gaussian mixture matrices, Multivariate AR modelling, hidden Markov models, fuzzy logic approach, linear discriminant methods, and so on [2-7]. However, SEMG measurement placement is also critical for recognition accuracy and evaluating the effect of SEMG measurement placement is important.

In this study, our objective is to evaluate the effect of SEMG measurement placement in hand motion recognition accuracy. Since measured SEMGs show huge differences depending on the individual structure of the muscle and the diversity of personal factors, it is quite difficult to decide the optimal SEMG measurement placement according to the theory. Thus, we employ the Monte Carlo method. We use a 96-channels matrix-type surface multielectrode and four channels are selected as the SEMG measurement placements from the 96-channels that compose multielectrode. The SEMG measurement placement that is composed of four channels is generated by randomly selected number and the total number of the SEMG measurement placement is 5,000. In order to also consider the influence of discriminant analysis, our system employs the linear discriminant analysis and nonlinear discriminant analysis. Each selected SEMG measurement placement is assessed by those two types of discriminant analysis and the results are compared with each other.

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II. Methods

A. 96ch Multielectrode and SEMG measurement system

The multi electrode is one of the features and the key of our system. 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 multielectrode is attached to the forearm. A photographs of a forearm with attached multielectrode and the structure of the multielectrode are shown in Fig.1. To fit a forearm, we use a flexible silicone gum 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.

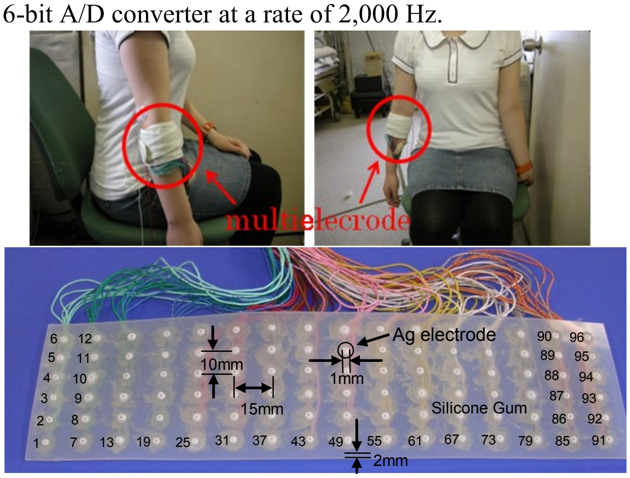


Fig.1 Upper figure shows a photographs of a forearm with attached multielectrode. And structure of 96-channles surface multi electrode. By the side of each electrode is shown the placement number from 1 to 96

B. Signal processing method

Our system applied two discriminant analyses to process the SEMG signals. These are the linear discriminant analysis and nonlinear discriminant analysis. Both analyses utilize four SEMG signals as an incoming signal.

1) Four channel Selection method:

In order not to lose a quick response of the system, it is necessary to use a smaller number of measurement channels. Since our previous study [7] shows that four SEMG channels are enough, we set the number of measurement channel to four. The configuration of four measurement channel is selected from multielectrode. And the configuration is determined using the Monte Carlo method and the Mersenne Twister method of random number generation [8]. We generated a set of 5,000 configurations and evaluated them.

2) Linear Discriminant Analysis:

The Canonical Discriminant analysis (CDA) is applied as a linear discriminant analysis. This discriminant analysis is a dimension-reduction technique and that makes a small number of canonical variate to clearly indicate the difference between each group

The SEMG feature extraction is performed by an integrated time and that is set to 300 ms [7]. Now, each component of feature extraction X_i is denoted by

$$X_i = c\sum_{n=1}^{N}\left|x_i(n\Delta t)\right| \tag{1}$$

where c is the constant for normalizing patterns, $x_i(t)$ is the sampled SEMG value at time t of i channel, and Δt is sampling period. The discriminant function Z is defined by

$$Z = \mathbf{a'}(X - \overline{X}) = \sum_{i=1}^{r} a_i (X_i - \overline{X}_i) \tag{2}$$

where $\mathbf{a'}$ is the transpose vector of $\mathbf{a}$, r is the number of components. As shown in equation (2), canonical variate Z is uniquely decided depending on coefficient vector $\mathbf{a}$.

Then, mean value of all group $\overline{X_i}^{(h)}$ as

$$\overline{X_i} = \sum_{h=1}^{g} n_h \overline{X_i}^{(h)} / n, \quad n = \sum_{h=1}^{g} n_h \tag{3}$$

where n is the total number of the data, and n_h is the number of the data in group h. Then, the within-groups variance-covariance matrix $\mathbf{W}$ of X_i is given by

$$\begin{aligned} &\mathbf{W} = (W_{ij}) \\ &W_{ij} = \sum_{h=1}^{g}\sum_{k=1}^{n_h}(X_{kj}^{(h)} - \overline{X_i}^{(h)}) \cdot (X_{kj}^{(h)} - \overline{X_j}^{(h)}) / (n-g) \end{aligned} \tag{4}$$

And the between-groups variance-covariance matrix $\mathbf{B}$ of X_i is given by

$$\begin{aligned} &\mathbf{B} = (B_{ij}) \\ &B_{ij} = \sum_{h=1}^{g} n_h (\overline{X_i}^{(h)} - \overline{X_i}) \cdot (\overline{X_j}^{(h)} - \overline{X_j}^{(h)}) / (g-1) \end{aligned} \tag{5}$$

Then, the within-group variance and between-group variance in equation (2) is given by

$$\begin{aligned} &S_w = \sum_{h=1}^{g}\sum_{k=1}^{n_h}(Z_k^{(h)} - \overline{Z}^{(h)})^2 / (n-g) = \mathbf{a'Wa} \\ &S_B = \sum_{h=1}^{g} n_h (\overline{Z}^{(h)} - \overline{Z})^2 / (g-1) = \mathbf{a'Ba} \end{aligned} \tag{6}$$

Vector $\mathbf{a}$ is calculated under the conditions of minimizing a correlation ratio $\lambda = S_B / S_W$. That is

$$\lambda = \frac{S_B}{S_W} = \frac{\mathbf{a'Ba}}{\mathbf{a'Wa}} \Rightarrow \max \tag{7}$$

From this condition,

$$(\mathbf{B} - \lambda\mathbf{W})\mathbf{a} = 0 \tag{8}$$

is derived. Exclude the $\mathbf{a} = 0$ state, it can be shown that

$$\left|\mathbf{W}^{-1}\mathbf{B} - \lambda\mathbf{E}\right| = 0 \tag{9}$$

where $\mathbf{E}$ is the unit matrix. Finally, we obtain the eigenvalue problem. The solution of equation (9) was calculated by a calculator and the coefficient vector $\mathbf{a}$ was obtained from the eigenvector corresponding to the obtained eigenvalue. Canonical variate Z was computed by equation (2) using the coefficient vector $\mathbf{a}$ and we obtained three Canonical variate Z_1, Z_2, Z_3. These constructed a discriminant space, and each motion group was classified by selecting a minimum Euclidean Distance based on this discriminant space.

3) Nonlinear Discriminant Analysis:

As a nonlinear discriminant analysis, we apply the multi-layer neural-type networks employing backpropagation algorithm (BPNN). This algorithm is one of the well-known method as an effective tool for nonlinear classification. Thus, we utilize this BPNN to recognize the intended motion.

Now, we build up three-layered neural networks. Input pattern which is the feature of SEMG is set to $\mathbf{x} = (x_1, x_2, \ldots, x_I)^T$. Input SEMG data is performed by an integrated time as well as CDA method. And output pattern which means the type of recognized motion is set to $\mathbf{z} = (z_1, z_2, \ldots, z_K)^T$. Then, our network is expressed as

$$\begin{aligned} \zeta_j &= \sum_{i=1}^{I} a_{ij} x_i + a_{0j} \\ y_i &= f_{hidden}(\zeta_j) \\ \eta_k &= \sum_{j=1}^{J} b_{jk} y_j + b_{0k} \\ z_k &= f_{out}(\eta_k) \end{aligned} \tag{10}$$

where y_j is the output of the *j*-th middle layer neuron. a_{ij} is a input connection weight and b_{jk} is a output connection weight. f_{hidden}, f_{out} are activation function. We apply the $sigmoid$ that defined by the expression

$$f(\eta) = \frac{1}{1 + \exp(-\eta)} \tag{11}$$

Now, put on training data $\{\mathbf{x_p}, \mathbf{u_p}\}$, and we utilize an error square function as follows

$$\varepsilon_{emp}^2 = \sum_{p=1}^{P} \left\| \mathbf{u_p} - \mathbf{z_p} \right\|^2 = \sum_{p=1}^{P} \varepsilon_{emp}^2(p) \tag{12}$$

(12) is evaluation criteria for training network. Calculation of the partial differential about connection weight of error square ε_{emp}^2 , we obtain

$$\begin{aligned} \frac{\partial \varepsilon_{emp}^2}{\partial a_{ij}} &= \sum_{p=1}^{P} \frac{\partial \varepsilon_{emp}^2(p)}{\partial a_{ij}} \\ \frac{\partial \varepsilon_{emp}^2}{\partial b_{jk}} &= \sum_{p=1}^{P} \frac{\partial \varepsilon_{emp}^2(p)}{\partial b_{jk}} \end{aligned} \tag{13}$$

Therefore, update connection weights are obtained by

$$\begin{aligned} a_{ij} &\Leftarrow a_{ij} - \alpha \frac{\partial \varepsilon_{emp}^2}{\partial a_{ij}} \\ b_{jk} &\Leftarrow b_{jk} - \alpha \frac{\partial \varepsilon_{emp}^2}{\partial b_{jk}} \end{aligned} \tag{14}$$

When the error(shown in equation (12)) is acceptably small for all of the training pattern pairs or the number of training exceeds the maximum training number, training can be discontinued.

III. Experimental Results and Discussion

We tested four normal subjects including two males and two females to evaluate our system. In order to investigate sensitive changes, we set 18 motions including 10 finger movements as requested motions. (Wrist Flexion, Wrist Extension, Grasp, Release, Radial Deviation, Ulnar Deviation, Pronation, Supination, Flexion of Index Finger, Flexion of Middle Finger, Flexion of Ring Finger, Flexion of Small Finger, Flexion of Thumb, Extension of Index Finger, Extension of Middle Finger, Extension of Ring Finger, Extension of Small Finger, Extension of Thumb).

The experiment was set up as follows:

1. Registration of the SEMG characteristic of the 18 motions for every subject. This data was used as "predefined data" for the both analyses.
2. Generation of 5,000 sets of configuration. Every configuration is calculated by two discriminant analysis and obtained own motion recognition rate respectively.
3. Comparison of the effect of CDA and BPNN. One configuration that shows best recognition rate is decided as an optimal SEMG measurement placement.

This study mainly investigates three topics:

A) Relationship between the number of requested motion and recognition accuracy.

B) Distribution of recognition rates computed using 5,000 sets of configuration.

C) Evaluation of recognition accuracy using an optimal configuration that decided by other discriminant analysis.

Table I shows experimental results of III-A. From this table, we can see that recognition rate of CAD achieved a high accuracy recognition compared with BPNN is used. Both recognition rates tended to decrease with the increase in the number of requested motions. The recognition rate shown with an underline in Table I is the maximum value in which a recognition accuracy exceeds 80%. Thus, in order to obtain the recognition accuracy exceeding 80% about subject A, 18 motions can be recognized when CDA is used and 6 motions can be recognized when BPNN is used. When the maximum rate was obtained, our system decides the used configuration as the optimal configuration for motion recognition.

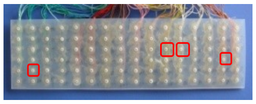
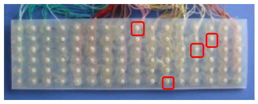
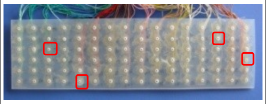
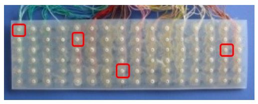
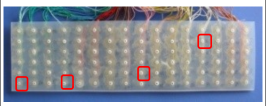
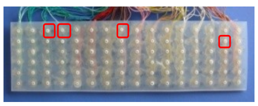
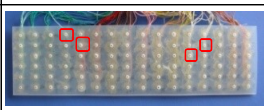
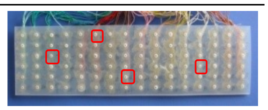
TABLE I

An Average of Each Motion Recognition Rates Depending on The Number of Requested Motions

The number of	Subject A		Subjec B		Subjec C		Subjec D	
requested motions	CDA	BPNN	CDA	BPNN	CDA	BPNN	CDA	BPNN
1 Motion	-	-	-	-	-	-	-	-
2 Motion	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
3 Motion	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
4 Motion	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
5 Motion	100.0	96.0	100.0	88.0	100.0	**80.0**	100.0	92.0
6 Motion	100.0	**83.3**	100.0	**80.0**	100.0	70.0	100.0	**83.3**
7 Motion	100.0	74.3	94.3	77.1	94.3	68.6	97.1	77.1
8 Motion	97.5	70.0	90.0	67.5	82.5	57.5	97.5	60.0
9 Motion	93.3	62.2	88.9	57.8	82.2	57.8	93.3	55.6
10 Motion	86.0	58.0	82.0	52.0	78.0	50.0	**80.0**	54.0
11 Motion	89.1	54.6	**81.8**	50.9	**80.0**	52.7	74.6	52.7
12 Motion	86.7	50.0	73.3	46.7	71.7	45.0	75.0	48.3
13 Motion	83.1	47.7	73.9	46.2	69.2	41.5	67.7	43.1
14 Motion	81.4	45.7	72.9	44.3	70.0	41.4	71.4	41.4
15 Motion	81.3	41.3	74.7	40.0	73.3	36.0	62.7	42.7
16 Motion	82.5	40.0	72.5	33.8	67.5	32.5	58.8	38.8
17 Motion	80.0	37.7	68.2	31.8	63.5	32.9	56.5	35.3
18 Motion	**82.2**	34.4	64.4	32.2	62.2	35.6	55.6	30.0

TABLE II

RED SQUARES ON MULTIELECTRODE SHOW A SELECTED FOUR CANNELS CONFIGURATION OF EACH SUBJECT AND THE NUMBER SHOWN BELOW SHOWS OPTIMAL CHANNEL NUMBER. PERCENTAGE SHOWS RECOGNITION RATE BASED ON OTHER DISCRIMINANT ANALYSIS USING SAME CONFIGURATION.

Subject	Type of discriminant analysis	
	CDA	BPNN
A	 (8, 64, 70, 87)	 (54, 61, 76, 83)
	If BPNN is used:18%	If CDA is used:18%
B	 (16, 25, 83, 93)	 (6, 29, 44, 88)
	If BPNN is used:33%	If CDA is used:60%
C	 (1, 19, 50, 77)	 (18, 24, 48, 89)
	If BPNN is used:9%	If CDA is used:56%
D	 (24, 29, 70, 77)	 (16, 36, 44, 75)
	If BPNN is used:10%	If CDA is used:70%

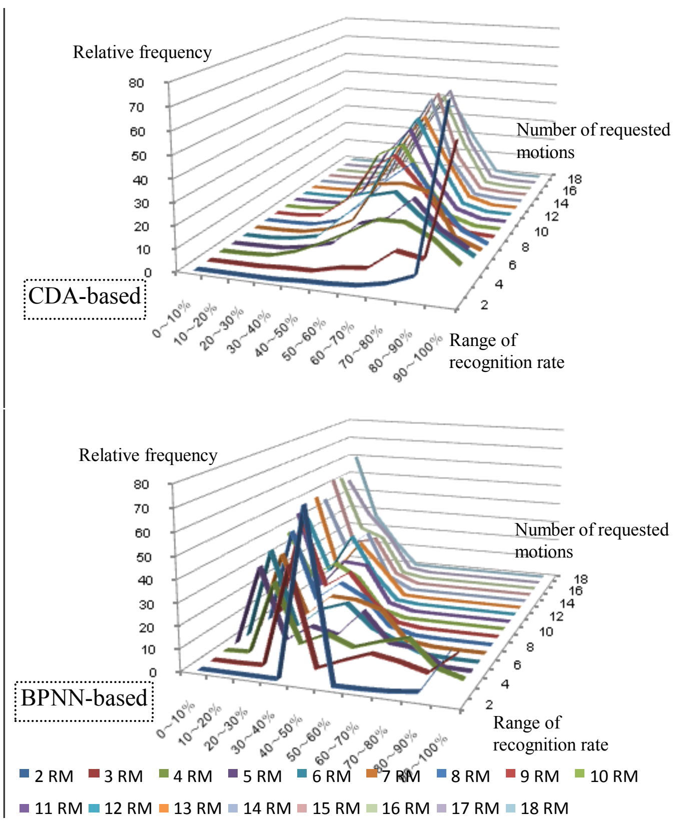


Fig.2 Relative frequency of recognition rate based on each number of requested motions. RM means Requested Motions. Upper figure shows CDA-based characteristic and lower figure shows BPNN-based characteristic.

Table II shows the optimal configurations (those are shown in table I) and calculate recognition rate using the other discriminant analysis. From table II, selected optimal configuration differed in every subject. Even if same subject was tested, the results showed a huge different configuration depending on discriminant analysis. Since we thought that those configurations can detect effective SEMG information, we evaluated a recognition accuracy that applied other discriminant analysis using same measurement configuration. Contrary to anticipation, the recognition accuracy was decreased. In the case of using CDA-based optimal configuration of subject A, recognition rate can be achieved to 82.2% using CDA, however, it can be achieved only to 18 % using BPNN. In the case of using BPNN-based optimal configuration, 83.3% is achieved by using BPNN and 18% is achieved by using CDA. Those results suggest that optimal configuration differs not only among subject but also among discriminant analysis. We would like to continue detailed investigation of this topic.

Fig.2 shows a relative frequency of recognition rate based on each number of requested motions. This figure was created by 5,000 sets of configuration and it showed the distribution of recognition rate for every number of requested motions. CDA-characteristic is expressed at relatively high levels in relative frequency. BPNN-characteristic was distributed in lower range of recognition rate and it had two peak of change characteristic. In spite of the experiment under the same condition, both characteristics differed widely.

The interpretation of this reason is our future interesting research and we'd like to wish this investigation is useful to develop SEMG system.

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