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Development of the human interface equipment based on surface EMG employing channel selection method

Kentaro NAGATA, *Student Member, IEEE,* Keiichi ANDO, Shinji NAKANO, Hideaki NAKAJIMA, Masafumi YAMADA, *Member, IEEE,* and Kazushige MAGATANI, *Member, IEEE*

Abstract— **In this paper, we describe the Human-Interface equipment using surface electromyogram (SEMG) based on optimal measurement channels for each subject. In case the SEMG is used as a control signal, individual differences of SEMG are important issue to obtain high accuracy recognition of motions. To solve this problem, we propose a channel selection method of the suitable measurement channels for the recognition of motions. We use a 96-channel matrix-type (6 × 16) surface electrode attached to the forearm in order to measure the SEMG generated from many active muscles during hand motions. From those 96 electrodes, our system decided the number of measurement channels and the position of measurement channels. This can be achieved by using the Monte Carlo method. Our system generates 10,000 sets of randomly selected channels, and these sets are evaluated by the recognition rate of hand motions. One set that records a highest recognition rate is selected from 10,000 sets for an optimal set of measurement channels. And the one set with the smallest number of measurement channels which fulfill the recognition rate above 90% or the maximum recognition rate above 95% is used for real-time recognition.**

Six normal subjects were experimentally tested using our system. The recognition rates of 18 hand motions, including 10 finger movements, were assessed for every subject. We were able to distinguish all the motions, and the average recognition rate in the real-time experiment was measured to be greater than 95%. And the number of selected channels ranged from 4 to 7.

I. Introduction

TODAY, the human interface is one of the key technologies for various fields. Especially, many systems which use surface electromyogram (SEMG) as a control signal have been reported by a lot of researchers, for example, assist system for the disabled[1], control of manipulator [2], prosthetic hand[3], and there is many applied examples[4-6].

High accuracy recognition of motions is a common requirement for those systems. However, in order to obtain high accuracy recognition of motions, individual differences of SEMG is an important issue. To solve this problem, a conventional method employs a strong recognition method such as a neural network [2]. Moreover, AR modeling [7], fuzzy logic approach [8] and several methods are also used as a classification method [9-11]. In those systems, the measurement channels position are fixed depending on effective muscles for movements. There may be the reason for this is that the muscles used for motions have become clear anatomically. However, SEMG which measures the electric signal from many muscles fibers is greatly different. It is caused by depending on the individual structure of the muscle, physical relationship of the electrode and end-plate band, and the diversity of personal factors. Therefore, we think that there is suitable measurement position for each subject to recognize the motions. And to make high accuracy recognition of the motions possible, the set to the suitable measurement position is required. A large number of studies have been carried out into the recognition of motions, little is known about the selection method of SEMG measurement position.

In this paper, the objective of our system is to obtain high accuracy recognition of the motions and a development of useful human interface using SEMG under any subject. To achieve this objective, it is not enough to only improve the classification method. Measurement channels also should be considered. Whereas we recognize the importance of the discriminant function, it is channel selection method that needs to be improved in recognition method. We will propose a recognition method of forearm motions based on SEMG employing channel selection method and try to verify this validity. And we present experimental results using this method.

II. System Design

An outline of our SEMG recognition system is shown in Fig.1. Our system is divided into three parts, the SEMG measurement part, the SEMG analysis part and the system operation part. In the SEMG measurement part, we measured SEMG of each motion from a 96-channels multielectrode. In the SEMG analysis part, the number of measurement channels and the position of measurement channels for each subject are selected with the application of the canonical discriminant analysis and the Monte Carlo method. Last operation part, discriminated SEMG is used as control signals to operate various kinds of systems.

A. 96-channels surface multielectrode

The multielectrode is one of the features of our system. The structure of this multielectrode is shown in Fig.2. This multielectrode is composed of 96 silver electrodes (16x6).

Kentaro NAGATA, Keiichi ANDO, Shinji NAKANO, Hideaki NAKAJIMA and Kazushige MAGATANI are with the Department of Electrical and Electronic Engineering , TOKAI University, JAPAN (e-mail: nagata@lachesis.ep.u-tokai.ac.jp).

Masafumi YAMADA is with Kanagawa Rehabilitation Institute, JAPAN (e-mail: masafumiyamada@hi-ho.ne.jp).

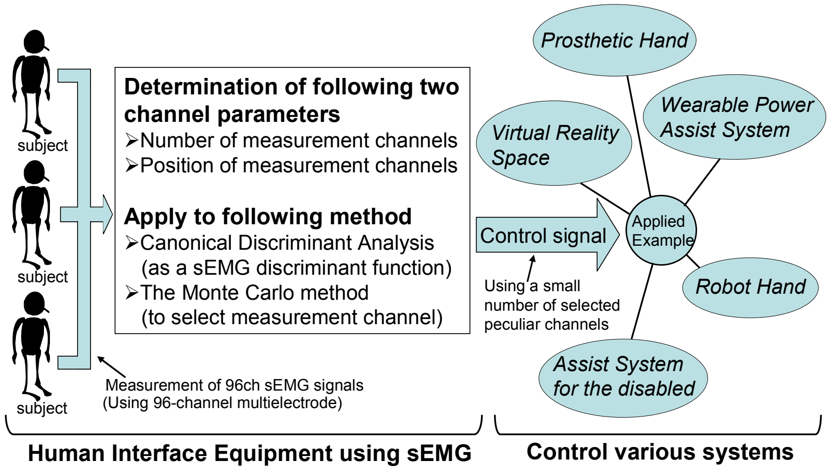


Fig. 1. Outline of our Human Interface Equipment using SEMG

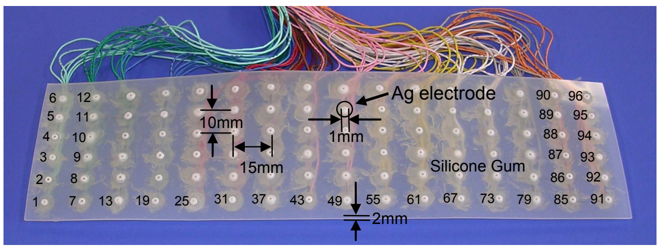


Fig.2 96-channles surface electrode. By the side of each electrode is shown the placement number from 1 to 96

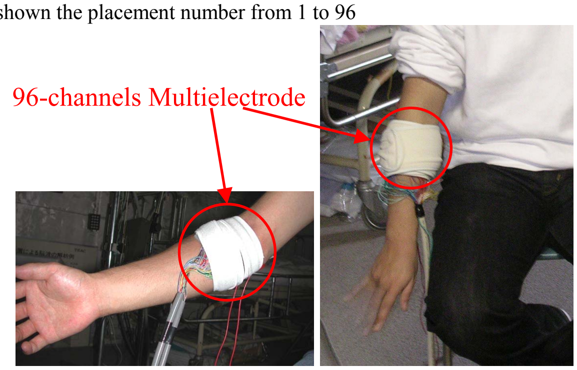


Fig.3 Placement of surface multielectrode

Each electrode is 1mm in diameter and that is arranged with an electrode interval, 10mm long and 15mm wide. To fit a forearm bodyline, we use a flexible silicone gum as the base of 96 silver electrodes. This electrode was attached to the forearm (Fig.3).

To measure the SEMG signals, we also developed SEMG Amplifier. We designed this system in which 3,000 times amplification is possible in effective frequency band of the SEMG. The frequency bandwidth is composed of a low-pass filter and a high-pass filter, and the cut-off frequencies are 1,000Hz (L.P.F.) and 10Hz (H.P.F.), respectively. The amplified SEMG signals are sampled by a 16-bit A/D converter at a rate of 2,000Hz.

B. Channel Selection Method

In consideration of operating some systems, an important thing is the reduction of measurement channels with high accuracy recognition of the motions. Using all 96 channels lose a quick response and a simple way. The studies of channel reduction are performed in some fields, such as BCI (Brain Computer Interface) [12]. However, there are few researches about channel reduction in motion recognition using SEMG. We think the cause is that it is not clear how valuation function can be selected to estimate SEMG measurement channels. In addition, the combination of a small number from 96 channels becomes huge.

Against this background, we do not select the strict SEMG measurement channels according to any valuation function, but we propose the method to use randomly selected number to estimate each channel. Therefore, we applied the Monte Carlo method for the channel selection. 10,000 times is set as the number of estimate trials. In case one and two for the measurement number is selected, all combination numbers are estimated. (i.e., each combination number (${}_{96}C_1$ and ${}_{96}C_2$) is less than 10,000). To generate randomly selected number, we applied the Mersenne Twister method [13]. The following is our proposed method. And block diagram of this method is shown in Fig.4.

Before proposing our method, we would like to consider about our precedence research result and SEMG discriminant function. The result shows the average of real-time recognition rate was measured to be greater than 90% using 16 measurement channels [14]. Thus, 16 channels are set as the maximum number of the measurement channels, and we select 16 channels at the most from 96 channels. About a SEMG discriminant function, we applied the Canonical Discriminant analysis. The SEMG feature extraction is performed by an integrated time (300 ms) [14].

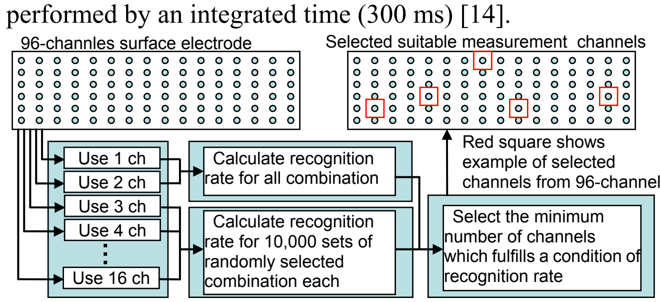


Fig.4 Schematic block diagram of channel selection method

This discriminant function is one of liner discriminant function and makes canonical variate that is the variate of small number showing the difference between groups. Generated canonical variates construct a discriminant space, and each motion group is classified by selecting a minimum Euclidean Distance.

C. Calculate Recognition Rate

Our channel selection method is composed of three stages. The first stage is to register the SEMG for each subject and five trials are performed to all requested motions as a pre-experiment. In this pre-experiment, the SEMGs are measured during 900 ms for a trial. The second stage is the calculation of 10,000 sets of recognition rate. The SEMG channel data corresponding to a randomly selected number is used. As mentioned earlier, SEMG feature extraction is performed by an integrated time. We make same integrated time data and that start point is shifted every 60 ms from the data during 900 ms (Fig.5). Therefore we obtain 10 sets of SEMG data for 300 ms. In the discriminant space that calculated by the first 300 ms data, how many motions can be recognized to these 10 sets data is evaluated as a recognition rate. Thus, we obtained 10,000 recognition rates of each number of measurement channels from 10,000 trials by each randomly selected channel. The last stage is selection of one measurement channels set. The set of each number of measurement channels that records the highest recognition rate from 10,000 sets is selected. To decide the number of measurement channels, we investigate the relationship between the number of measurement channels and the recognition rate in six normal subjects. Fig.6 shows the result of this relationship.

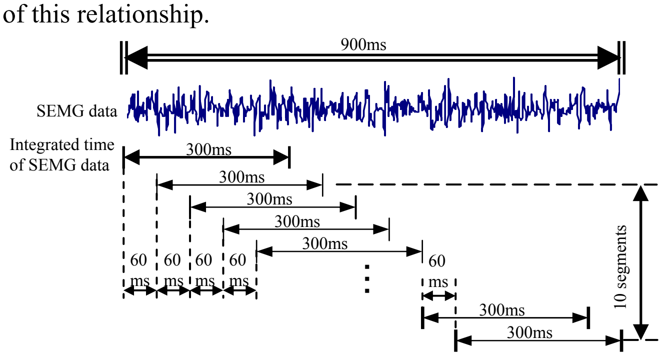


Fig.5 SEMG data segmentation for the calculation of recognition rate

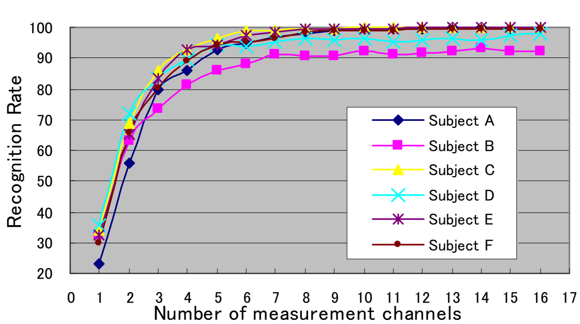


Fig. 6. Relationship between the number of measurement channels and recognition rate in pre-experiment.

From Fig.6, we can see a saturation point of the recognition rate for each subject. Thus, it is thought that the number of measurement channels more than a certain number is redundant. In order to decide the number of measurement channels, we set the threshold value of recognition rate for channel selection. We propose two types of values as follows.

A) Recognition rate of greater than 90 %
B) Maximum recognition rate for the subject of greater than 95 %

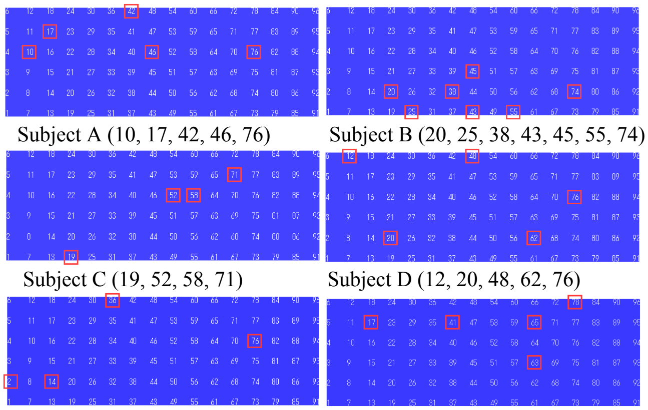
We investigate the minimum number of measurement channels which fulfills each condition. If no rate is suitable for requirement of type (A) (i.e., there is no recognition rate of greater than 90 % in 1 to 16 measurement channels.), an only type (B) that is using individual maximum recognition rate is adopted. After this processing, we compare the number of measurement channels of type (B) with the number of measurement channels of type (A). Default of the number of measurement channels is selected by type (B), however, the number of measurement channels of type (A) is selected if the number of type (A) is under the number of type (B). This number of measurement channels set and the position of channels are decided to use in real-time recognition. Table I shows the results of this selecting method and the selected measurement channels for each subject are represented by underline. Each selected channel positions are shown in Fig.7. The red square in Fig.7 shows selected channels for each subject. From this figure, we find the huge difference in the position of selected measurement channels including the number of measurement channels. It is thought that the results prove they have individual suitable measurement positions.

III. Real-Time Recognition Experiment

In order to evaluate our system, six normal subjects were tested. In order to recognize sensitive difference, 18 motions that contain 10 finger movements (see Table II) are set as requested motions. These motions that put a stress on daily activity are selected. The results in real-time experiments are shown in Table II. The recognition rates are calculated by each 10 trials.

TABLE I
Selected Number of Measurement Channels
Using Two Types Of Channel Selection Method

Subject (Individual maximum recognition rate)	Selected number of measurement channels	
	Type A	Type B (Required recognition rate)
Subject A (100%)	**<u>5 channels</u>**	7 channels (greater than 95%)
Subject B (93.1%)	7 channels	**<u>7 channels</u>** (greater than 88.4%)
Subject C (100%)	**<u>4 channels</u>**	5 channels (greater than 95.0%)
Subject D (97.7%)	5 channels	**<u>5 channels</u>** (greater than 92.8%)
Subject E (100%)	**<u>4 channels</u>**	6 channels (greater than 95.0%)
Subject F (99.6%)	**<u>5 channels</u>**	6 channels (greater than 94.6%)



Subject A (10, 17, 42, 46, 76) Subject B (20, 25, 38, 43, 45, 55, 74)

Subject C (19, 52, 58, 71) Subject D (12, 20, 48, 62, 76)

Subject E (2, 14, 36, 76) Subject F (17, 41, 63, 65, 78)

Fig.7 Map of selected measurement channels for each subject. The inside of a parenthesis shows the placement number of selected channel. This number is correspondence with the number of Fig.2

TABLE II
REAL-TIME RECOGNITION RATES OF 18 MOTIONS

	Recognition Rate (%)					
Requested Motion	**A**	**B**	**C**	**D**	**E**	**F**
Wrist Flexion	100	100	100	100	100	90
Wrist Extension	100	90	100	100	90	100
Grasp	100	100	100	100	100	100
Release	100	100	100	90	100	100
Radial Deviation	90	100	90	100	100	100
Ulnar Deviation	100	100	100	100	100	100
Pronation	80	100	100	100	100	100
Supination	100	90	100	90	100	80
Flexion of Index Finger	90	100	90	100	90	100
Flexion of Middle Finger	90	100	100	90	100	90
Flexion of Ring Finger	100	80	100	100	100	100
Flexion of Small Finger	90	70	100	100	100	100
Flexion of Thumb	90	90	100	90	100	90
Extension of Index Finger	100	100	90	100	90	100
Extension of Middle Finger	100	90	100	90	100	100
Extension of Ring Finger	100	100	100	90	80	90
Extension of Small Finger	90	100	100	100	100	100
Extension of Thumb	100	100	90	100	100	90
Average	**95.6**	**95.0**	**97.8**	**96.7**	**97.2**	**96.1**

Experimentally, we can discriminate 18 hand motions of the hand including 10 finger movements by employing the proposed method. Moreover, the average recognition rates in the real-time experiments were measured to be greater than 95 %. And the numbers of selected channels were 5, 7, 4, 5, 4 and 5 respectively.

IV. CONCLUSION

In this paper, we described about the recognition method using channel selection as the human interface equipment based on surface EMG.

The proposed SEMG discriminant method differs greatly from others in that we select suitable SEMG measurement positions for each subject. We thought one of the most effective points to obtain high accuracy recognition rate is SEMG measurement position. And our system was designed under this concept. Using our system, selecting particular muscle and knowledge of SEMG are unnecessary. Only attaching this multielectrode, our system searches some useful measurement channels to recognize the motions automatically. In addition, we think that this selection method using a randomly selected number has the possibility of application to that system which requires channel selection.

From real-time recognition experiments, our system was able to achieve accurate classification of 18 motions using optimal measurement channels. The proposed method indicated to be useful in controlling several systems as a human interface.

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