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Application of least square method for muscular strength estimation in hand motion recognition using surface EMG

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Abstract—**In this study, we describe the application of least square method for muscular strength estimation in hand motion recognition based on surface electromyogram (SEMG). Although the muscular strength can consider the various evaluation methods, a grasp force is applied as an index to evaluate the muscular strength. Today, SEMG, which is 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. In SEMG system, to achieve high accuracy recognition is an important requirement. Conventionally SEMG system mainly focused on how to achieve this objective. Although it is also important to estimate muscular strength of motions, most of them cannot detect power of muscle. The ability to estimate muscular strength is a very important factor to control the SEMG systems. Thus, our objective of this study is to develop the estimation method for muscular strength by application of least square method, and reflecting the result of measured power to the controlled object. Since it was known that SEMG is formed by physiological variations in the state of muscle fiber membranes, it is thought that it can be related with grasp force. We applied to the least-squares method to construct a relationship between SEMG and grasp force. In order to construct an effective evaluation model, four SEMG measurement locations in consideration of individual difference were decided by the Monte Carlo method.**

I. Introduction

Electromyography is measuring the electrical signal associated with the activation of the muscle. Electromyography 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[3-20]. In order to apply it simply, the surface electromyogram (SEMG) which is measured from the skins surface, is widely used as a control source for human interface such as myoelectric prosthetic hands[4,5,11,13,16].

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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. About an 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, which is an essential requirement, and estimation of muscular strength are both 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. We think the ability to estimate muscular strength is also an important factor in controlling it. And furthermore, in consideration of simplicity and easy of use in using the SEMG interface, construction of simple discriminant model with a small number of measurement electrodes have been one of an SEMG interface’s main requirement.

In this study, our objective is to develop the estimation method for muscular strength while maintaining the accuracy of hand motion recognition and to reflect the result of the measured power on the controlled object. In order to achieve this objective, we directed our attention to measuring sufficient amounts of information for SEMG. This is because, the disadvantages of SEMGs are that they have a large detection area and therefore, have more potential for cross talk from adjacent muscles. Each subject’s SEMG greatly differed depending on the individual’s tissue characteristics, physiological cross talk and so on. Therefore, it is a problem if a fixed common measurement condition is applied to all subjects. We think that there is a suitable measurement location for every subject, and it is more effective for solving individual differences than employing strong discriminant models. This work proposes an application method of two simple linear models, and the selection method of optimal electrode configuration for using them effectively. The selection method has been one of our main objectives. About the number of measurement electrodes, our current work shows “four electrodes” are satisfactory to our objective [10]. In order to perform the selection of optimal measurement electrode configuration, a 96ch multi electrode is required to be able to measure an individual’s differences for SEMG.

II. SYSTEM DESIGNS

Our experimental system is divided into three stages. The first stage is the measurement of SEMG using multichannel electrode. As for SEMG measurement, almost all SEMG information about motion needs to be measured from the forearm. Second stage is SEMG signal processing. In this stage, we construct a discriminant analysis for motion recognition and the least square method for grasp force estimation. Final stage is evaluation of experimental results. Evaluation is performed by comparison of estimated grasp force value and real measured grasp force value.

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.

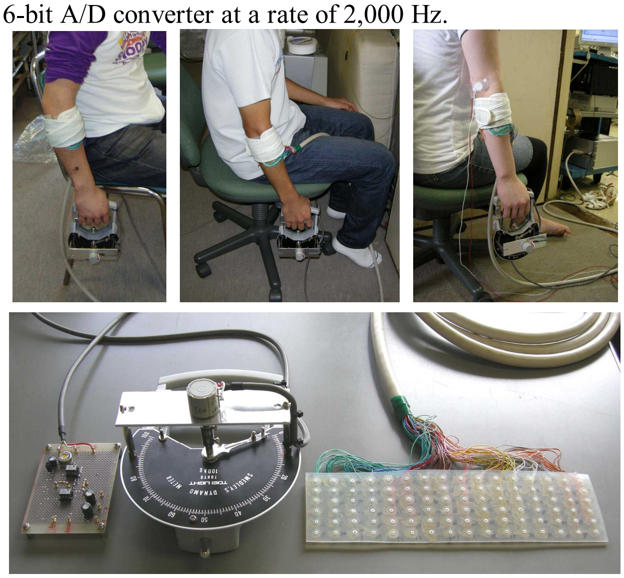

Fig.1 Upper photoprahies show images of a forearm with attached multielectrode. Lower photograph shows our experimental equipment. Left side is measuring equipment for PC input and the resistance-to-voltage converter. Right side is 96-channels matrix-type surface multielectrode.

B. Grasp force measurement system

In order to estimate a grasp force based on an SEMG signal, it is necessary to determine the relationship between the SEMG characteristic of grip and a real grasp force for every individual. In the case of most measurement equipment for grasp force, the measured value is indicated by a needle that moves over a dial gauge, and as a result the acquired grasp data cannot be stored into a personal computer (PC). To analyze the relationship using a PC, we developed a grasp force measurement system that provides a real time grasp force measurement and the output data is stored on a PC with the SEMG simultaneously.

A potentiometer is attached to the axis of rotation of the indicator, and translates the indicated value on the dynamometer into a resistance value. The resistance is converted to voltage using a resistance-to-voltage converter which we made. And the analog output voltage is converted to digital for PC input. Most dynamometers indicate only the maximum grasp force, but our equipment directly indicates the change of grasp. Fig.1 shows measuring equipment for grasp force and the resistance-to-voltage converter.

C. Linear Discriminant Analysis (Canonical Discriminant Analysis)

In order to discriminate the SEMG, we composed the pattern recognition system. Our system consists of three steps, feature extraction step, discriminant stage and classification stage. 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.

Next, we constitute the discriminant function. We use "Canonical Discriminant Analysis" to decipher the EMG patterns. This discriminant function which makes a correlation ratio the maximum is extensible on condition that $g(>2)$ groups. In general, to classify $g(>2)$ groups, $g(g-1)/2$ discriminate functions are required. In case of many groups for being classified exist, a long calculation time is required. It means that the system loses a quick response and useful way to use. Therefore, we use the canonical discriminant analysis. An importance of this method is clear expression of the difference of each group. using a small number of canonical variate. The pattern class is decided by this canonical variate. And we decided to use three Canonical variates.

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 $\mathbf{a}$. Vector $\mathbf{a}$ is calculated under the conditions of minimizing a correlation ratio. Finally, we obtain the eigenvalue problem. The solution of this problem was calculated by a calculator and the coefficient vector **a** was obtained from the eigenvector corresponding to the obtained eigenvalue. Canonical variate Z was computed by equation (2) using the coefficient vector **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.

D. Grasp force estimation with least square method

It is well known that there is a close relationship between the muscular force and the EMG signal (e.g., the dependence of the EMG/force ratio from angle position which can be eliminated by normalization of the MVC of force [1], and EMG/force ratios of three different muscles for MVC normalized EMG and force output data [2]). However, a considerable issue of this relationship is the individual's characteristics. Thus, our system applies a personal EMG/force relationship depending on the individual's muscle characteristics. In order to construct the relation between SEMG and grasp force, we decide to apply the least square method. This method is well known technique that is used to compute estimation of parameters and fit data.

Now, the relationship is written by

$$\hat{Y} = a + bX \tag{3}$$

where $\hat{Y}$ is the grasp force data which is performed as the dependent variable, and X is the features of SEGM which is performed as an independent variable.

This(3) equation involves two free parameters which specify the intercept (a) and the slope (b) of the regression line.The least square method defines the estimate of these parameters as the values which minimize the sum of the squares between the measurements and the model. This amounts to minimizing the expression:

$$\varepsilon = \sum_i (Y_i - \hat{Y}_i)^2 = \sum_i \left[Y_i - (a + bX_i)\right]^2 \tag{4}$$

where ε stands for "error" which is the quantity to be minimized. Taking the derivative of ε with respect to a and b and setting them to zero gives the following set of equations

$$\frac{\partial \varepsilon}{\partial a} = 2Na + 2b\sum X_i - 2\sum Y_i = 0 \tag{5}$$

and

$$\frac{\partial \varepsilon}{\partial b} = 2b\sum X_i^2 + 2a\sum X_i - 2\sum Y_i X_i = 0 \tag{6}$$

Solving these 2 equations gives the least square estimates of a and b as:

$$a = M_Y - bM_X \tag{7}$$

and

$$b = \frac{\sum (Y_i - M_Y)(X_i - M_X)}{\sum (X_i - M_X)^2} \tag{8}$$

The result of the relationship between the SEMG and the grasp force is shown in Fig.2.

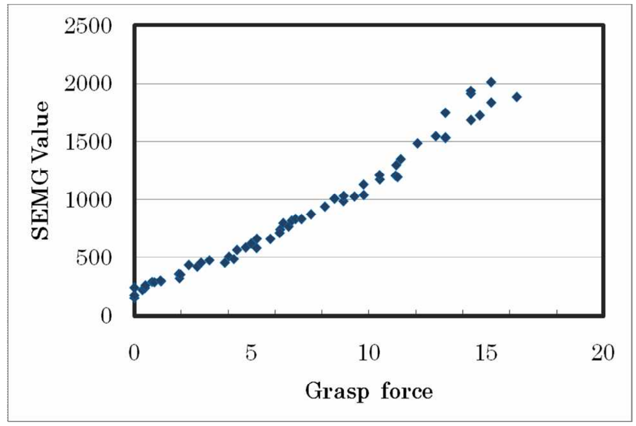

Fig. 2 **Relationship between the SEMG signals and measured Grasp force**

III. Experimental Results and Discussion

We tested five normal subjects to evaluate our system. Requested motions were set to four types which were composed of three motions and one state (Grasp, Release, Wrist Flexion and Rest state). The rest state is relaxed and there is no motion. This is the initial state and recognition of the three motions is started after this state. The recognition was performed by every 300 ms, and once a grasp motion is recognized, our system moves to the grasp force estimation mode. While a grasp motion is recognized, our system keeps evaluating the grasp force. As for the motions, each subject received training to get used to the control of our system. However, we didn't instruct the subject how to operate the system. Instead, they performed in their own way according to their individual's characteristics.

The experiment was set up as follows:

1. Registration of the SEMG characteristic of the four motions for every subject. This data was used as "predefined data"for the both modeling.
2. Selection of best configuration of four measurement electrodes
3. Construction of estimation model and comparison with a real measured grasp data

According to this procedure, the estimation experiment was performed. Fig.3 shows the comparison results of grasp force data between the estimated value and the real measurement one. From fig.3, the estimated value of the grasp force is a good approximation to the real one.

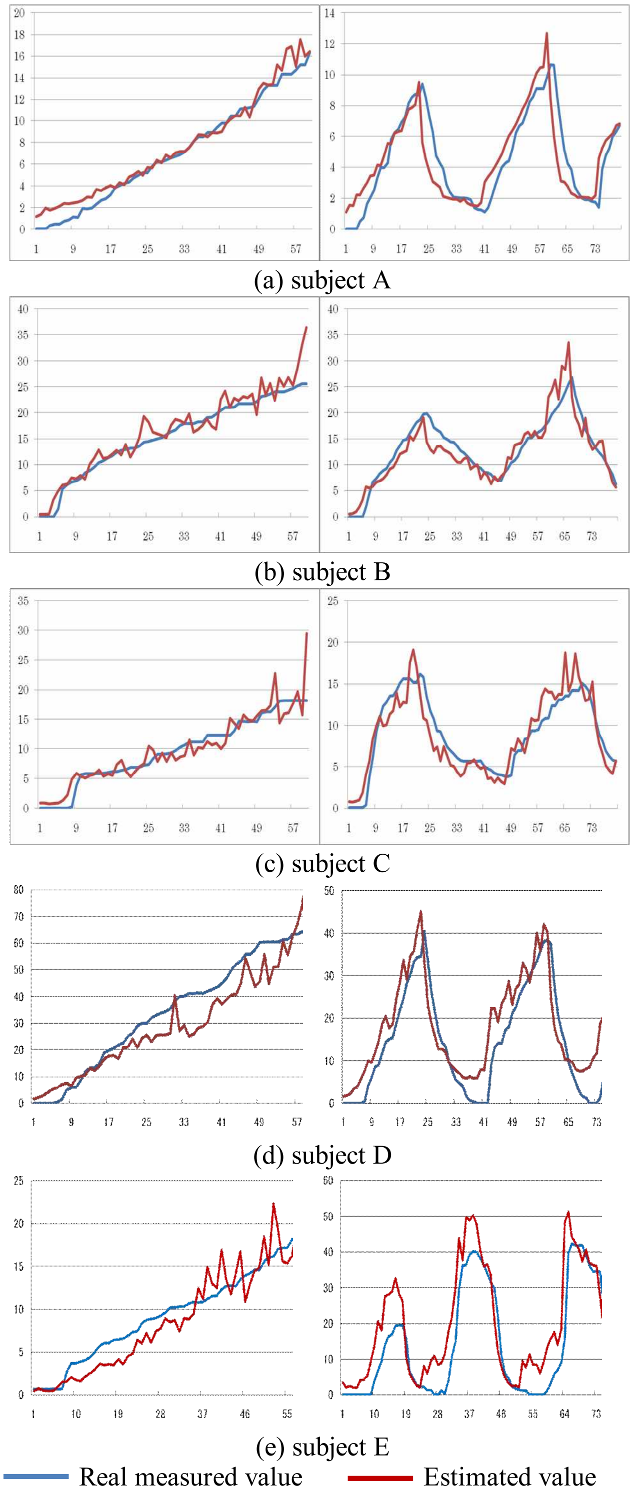

Fig. 3. The grasp force data of the estimated value and the real measurement value. The horizontal line shows the time series and vertical line shows the grasp force [kgf].

IV. CONCLUSION

We have presented an estimation method for muscular strength while maintaining the accuracy of hand motion recognition, and experimental results shows the recognition of four motions were perfect and the grasp force estimated results fit well with the real measured.

REFERENCES

[1] Basmajian, J and C. DeLuca, *Muscles Alive: Their Functions. Revealed by Electromyography*, Williams & WilkIns, 1985

[2] US Department of Health and Human Services, *Selected Topics in Surface Electromyography for Use in Occupational Settings: Expert Perspectives* , DHHS NIOSH Publications

[3] D.Staudenmann, I.Kingma, D.Stegeman, and J.Vandieen, “Towards optimal multi-channel EMG electrode configurations in muscle force estimation: a high density EMG study,” *Journal of Electromyography and Kinesiology*, vol.15, no 1, pp. 1 - 11, 2005.

[4] B. Hudgins, P. Parker, and R. N. Scott, “A newstrategy for multifunction myoelectric control,” *IEEE Trans. Biomed. Eng.*, vol. 40, pp.82–94, Jan. 1993.

[5] H.-P. Huang, and C.-Y. Chen “Development of a Myoelectric Discrimination System for a MultiDegree Prosthetic Hand,” in *Proc. 1999, Int. Conf. IEEE on Robotics & Automation* , Detroit, Michigan May 1999

[6] K. Nagata, M. Yamada, and K. Magatani, “Development of the assist system to operate a computer for the disabled using multichannel surface EMG,” in *Proc. 26th Ann. Int. IEEE Conf. Eng. Med. Biol.*, San Francisco, 2004, pp.4952-4955

[7] Y. Barniv, M. Aguilar, and E. Hasanbelliu, “Using EMG to anticipate head motion for virtual-environment applications” *IEEE Trans. Biomed. Eng.*, vol. 52, pp.1078-1093, June 2005.

[8] C. Choi, S. Micera,J. Carpaneto, and J. Kim, “Development and quantitative performance evaluation of a noninvasive EMG computer interface,” *IEEE Trans. Biomed. Eng.*, vol.56, no.1, pp. 188 - 191, Jun. 2009.

[9] R. F. Weir, P. R. Troyk, G. A. DeMichele, D. A. Kerns, J. F. Schorsch, and H. Maas, “Implantable Myoelectric Sensors (IMESs) for Intramuscular Electromyogram Recording,” *IEEE Trans. Biomed. Eng.*, vol.56, no.1, pp. 159 - 171, Jun. 2009.

[10] K. Nagata, T. Nakano, K. Magatani, and M. Yamada, “Estimation of muscle strength during motion recognition using multichannel surface EMG signals,” in *Proc. 30th Ann. Int. IEEE Conf. Eng. Med. Biol.*, Vancouver, 2009, pp. 351 - 354

[11] Y. Al-Assaf and H. Al-Nashash, “Surface myoelectric signal classification for prostheses control,” *J. Med. Eng. Technol.*, vol. 29, pp. 203–207, Sep./Oct. 2005.

[12] P. J. Gallant, E. L. Morin, and L. E. Peppard, “Feature-based classification of myoelectric signals using artificial neural networks,” *Med. Biol. Eng. Comput.*, vol. 36, pp. 485–489, Jul. 1998.

[13] Y. Huang, K. B. Englehart, B. Hudgins, and A. D. Chan, “A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses,” *IEEE Trans. Biomed. Eng.*, vol. 52, no. 11, pp. 1801–1811, Nov. 2005.

[14] Xiao Hu and Valerity Nenov, “Multivariate AR modeling of electromyography for the classification of upper arm movement” *Clinical Neurophysiology* 115, 1276-1287, 2004

[15] A. D. Chan and K. B. Englehart, “Continuous myoelectric control for powered prostheses using hidden Markov models,” *IEEE Trans. Biomed. Eng.*, vol. 52, no. 1, pp. 121–124, Jan. 2005.

[16] F. H. Y. Chan, Y. S. Yang, F. K. Lam, Y. T. Zhang, and P. A. Parker, “Fuzzy EMG classification for prosthesis control,” *IEEE Trans. Rehab. Eng.*, vol. 8, pp. 305–311, Sep. 2000.

[17] Yamada M, Niwa N and Uchiyama A “Evaluation of a Multifunctional Hand Prosthesis System Using EMG Controlled Animation” *IEEE Trans. Biomed. Eng.* vol.30, no.11, pp. 759-763, Nov. 1983

[18] K. Englehart, B. Hudgins, and P. A. Parker, “A wavelet-based continuous classification scheme for multifunctionmyoelectric control,” *IEEE Trans. Biomed. Eng.*, vol. 48, no. 3, pp. 302–311, Mar. 2001.

[19] P. Herberts, C. Almstrom, and K. Caine, “Clinical application study of multifunctional prosthetic hands,” *J. Bone Joint Surg. Br*, vol. 60-B, pp. 552–560, Nov. 1978.

[20] K. Nagata, K. Ando, K. Magatani, and M. Yamada, “Development of the hand motion recognition system based on surface EMG using suitable measurement channels for pattern recognition,” in *Proc. 29th Ann. Int. IEEE Conf. Eng. Med. Biol.*, Lyon, 2007, pp. 5214 - 5217

[21] Matsumoto M, Nishimura T: “Mersenne Twister A 623-dimensionally equidistributed uniform pseudorandom number generator”. *ACM Trans. on Modeling & Computer Simulation.* vol.8, no.1, pp.3-30, January 1998.