33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Optimal Measurement Position Estimation by Discriminant Analysis based on Wilks' lambda for Myoelectric hand Control

Atsushi Kiso, Yu Taniguchi and Hirokazu Seki, Member, IEEE

Abstract— **This paper describes an optimal measurement position estimation by the discriminant analysis based on Wilks' lambda for the myoelectric hand control. In the past studies, the myoelectric signals were measured from the same positions for the motions discrimination. However, the optimal measurement positions of the myoelectric signals for the motion discrimination are different according to the remaining muscle situation of amputees. Therefore the purpose of this study is to estimate the optimal and fewer measurement positions for the precise motion discrimination of the human forearm. This study proposes the estimation method of the optimal measurement positions by the discriminant analysis based on Wilks' lambda among the myoelectric signal measured from multiple positions. Some experiments on the myoelectric hand simulator show the effectiveness of the proposed optimal measurement position estimation method.**

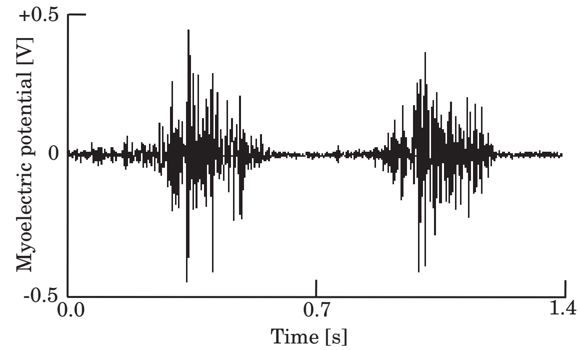


Fig. 1. Example of myoelectric potential waveform.

I. INTRODUCTION

In the modern society where the safe management and accident prevention are recognized enough, there are many people losing their arms by traffic accidents or disaster. Therefore the development of artificial arm having a same function as lost arm is expected. Many studies have been performed involving electromyogram (EMG) signals to control robotic artifacts, such as prosthetic hand, arm and upper limb.

The EMG is a record of the myoelectric potential that muscular fiber conduct in response to a motion command. Therefore the EMG includes the motion command information. Fig.1 shows an example of EMG waveform. Highly precise pattern analysis processing is necessary to estimate the motion intention from EMG. In the several studies, the neural network has been often used and realizes the high discrimination precision.

In the past, several studies of the human forearm motion discrimination based on the myoelectric signal have been conducted. As such, the backpropagation based on the frequency information of the myoelectric potential [1], the neural network based on the statistics structure [2] [3], the concise neural network by the optimization of input data and learning data [4], the adaptive fuzzy inference using the average value and the standard deviation of the myoelectric signals [5], the pattern analysis based on the reconfiguration possibility hardware and the genetic algorithm [6], the recognition of hand motions based on multi-channel sEMG using Monte Carlo method for channel selection [7], the neural network based on the principal component analysis of the frequency information [8], and a new learning method of Gaussian mixture models (GMMs) to improve the EMG pattern recognition accuracy [9] have been researched. In other studies, hidden Markov model (HMM) [10] [11], neural network [12], fuzzy inference [13]-[16] and linear discriminant analysis (LDA) [17] [18] have been used.

In the past studies, motions were identified by measuring the myoelectric signals at the same positions. However, the optimal measurement positions of the myoelectric signals for the motion discrimination are different according to the remaining muscle situation of amputees. Therefore the myoelectric potential should be measured at the optimal positions of each users. In addition, because the use of many myoelectric sensors is not realistic due to the cost and the amputating situation of the human forearm, the motion should be identified with smaller number of myoelectric sensors. Then, there is a possibility that the motions can be identified with smaller number of myoelectric sensors by measuring the myoelectric potential at the optimal positions statistically selected. Therefore the purpose of this study is to estimate the optimal measurement positions for the motion discrimination and to obtain high discrimination precision of the human forearm motions.

In the recent study, the selection of the myoelectric sensor by the variable selection method based on the partial KL information measure [19], the investigation of the optimum electrode locations by using an automatized surface EMG analysis technique [20] and an electrode selection algorithm for the high density EMG recordings [21] are researched. This study proposes the estimation method of the optimal measurement positions by the discriminant analysis based on Wilks' lambda from the myoelectric signals measured from multiple positions.

A. Kiso, Y. Taniguchi and H. Seki are with Electrical, Electronics and Computer Engineering, Chiba Institute of Technology, Chiba 275-0016, Japan (corresponding author to provide phone: +81-47-478-0378; fax: +81-47-478-0299; e-mail:s0979503KM@it-chiba.ac.jp;)

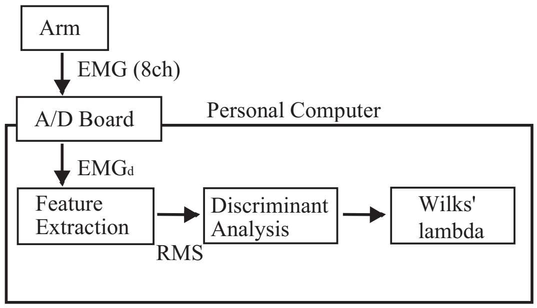


Fig. 2. Configuration of the optimal measurement position estimation method.

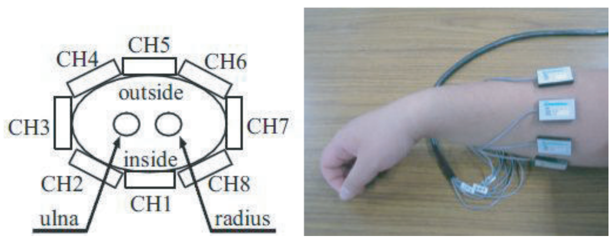


Fig. 3. Myoelectric sensors of eight channels are assigned every 45 degrees to the forearm.

II. Optimal Measurement Position Estimation by Discriminant Analysis based on Wilks' lambda

A. Summary

The configuration of the optimal measurement position estimation method appears in Fig.2. The myoelectric signals are measured from eight positions for the estimation of the optimal measurement positions. The optimal measurement positions are selected from these eight channels by the discriminant analysis based on Wilks' lambda.

In this study, six types of motion, "Open", "Grasp", "Flexion", "Dorsiflexion", "Pronation" and "Supination" are applied as the identification target motions.

B. Measurement of Myoelectric Potential

The measurement of the myoelectric potential uses a dry process myoelectric sensor SX230 made in Biometrics Company of eight channels. The amplification rate is 1000 times, and the bandwidth is 20Hz - 460Hz. This myoelectric sensor has the third Butterworth filter (a high pass filter of 20Hz) and the eighth coalition Chebyshev filter (a low pass filter of 460Hz) built-in. The measured myoelectric potential is input to the PC after making A/D conversion (sampling period 1kHz). The myoelectric potential input into a PC draws a waveform in an application manufactured by Visual C++.net 2003.

The myoelectric sensors of eight channels are assigned every 45 degrees to the forearm of the subject (cf. Fig.3). Because there are "flexor digitorum muscle, flexor carpi radialis muscle and flexor carpi ulnaris muscle, etc." used for the identification target motions, the myoelectric potential is measured as shown in Fig.3. Then there is a possibility that the muscles used for the forearm motions are different from healthy people according to the amputating situation. Therefore the optimal measurement positions for the motion discrimination are different according to the remaining muscle situation of amputees. In addition, there is a possibility that the measurement from the neighborhood of the muscular motor point becomes difficult by the below-elbow amputation. Therefore, this study doesn't measure from the neighborhood of the motor point and selects the optimal positions from eight electrodes allocated on the arm at regular intervals.

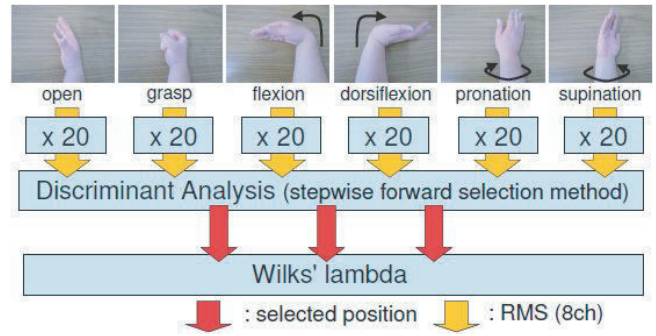


Fig. 4. Process of the optimal position estimation.

C. Feature Extraction

This study uses the root mean square (RMS) that shows the power of a signal for the feature quantity. The RMS can appropriately measure the signal with many noises, the signal of non-periodicity, and the signal of non-sinusoidal waves. In addition, the RMS maintains appropriate information more than the EMG is rectified or integrated [22]. And the RMS doesn't receive the influence by the superposition of a series of the action potential of the motor unit. Therefore only RMS is used for the feature quantity. The RMS is defined as the following equation.

$$RMS(t) = \sqrt{\frac{1}{2T}\sum_{\tau=-T}^{T} e^2(t+\tau)} \qquad (1)$$

The symbol $e(t)$ is the myoelectric potential signal and ($-T$,$+T$) is a calculation interval. Because there is the electromechanical delay (EMD) till the muscle generates power from the generation of EMG, the myoelectric potential is generated about 100ms before the muscle generates the power [23]. The motion discrimination should be finished within this 100ms so that prosthetic hand users does not feel the delay. Therefore the calculation period is set to 70ms in consideration of the calculation time of the identification processing.

D. Estimation of Optimal Measurement Position by Discriminant Analysis based on Wilks' lambda

The discriminant analysis is a method to distinguish the data groups that are known to belong to given group in advance. Therefore, in this study, 20 pairs of the RMS values of eight channels are prepared for each identification target motion (cf. Fig.4) and each motion groups are distinguished.

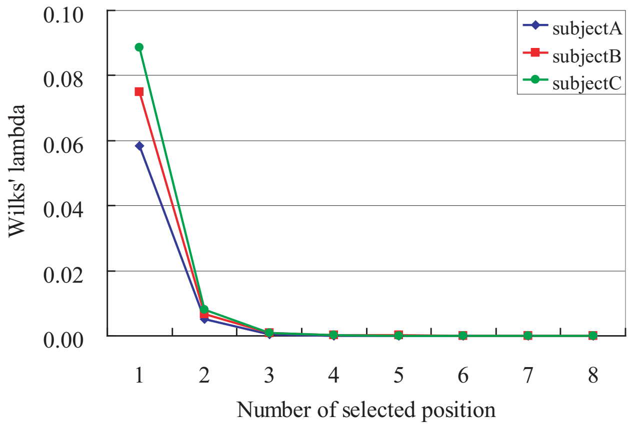
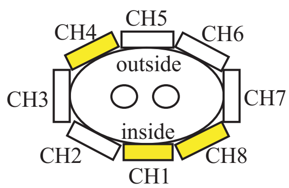
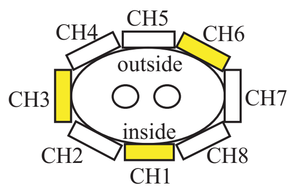


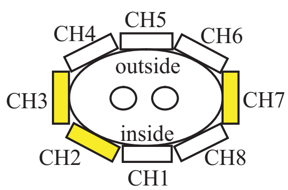
Fig. 5. Wilks' lambda by the number of selected positions.



(a) subject A (CH 1,4,8).



(b) subject B (CH 1,3,6).



(c) subject C (CH 2,3,7).

Fig. 6. Optimal measurement positions are selected by the stepwise selection. Three channels were selected in all subjects.

In addition, the motion groups are distinguished according to Mahalanobis' generalized distance. Then the optimal measurement positions are selected by the stepwise forward selection method. The selection criterion of the measurement position is set to $p_{in} = p_{out} = 0.05$. The discriminant precision at the selected positions is confirmed by Wilks' lambda. Wilks' lambda is an examination of the difference of the average value extended to the multivariate. Wilks' lambda is shown as the following equation.

$$\Lambda = |W|/|T| \tag{2}$$

T is total sum of squares and products matrix and W is within-groups sum of squares and products matrix. The following equation show the increase of the discriminant precision when new variable x_j was added to variable x_p.

$$\Lambda(x_j|x_p) = \Lambda(x_j,x_p)/\Lambda(x_p) \tag{3}$$

The numerator of right-hand side shows the lambda by x_j and x_p. The denominator shows the lambda by x_p. Wilks' lambda becomes the value between from 0 to 1. If the value is close to 0, the discriminant precision is high.

This study estimates the optimal measurement positions by three healthy people (subject A, B, C). Fig.5 shows the values of Wilks' lambda by the number of selected positions. Whenever the selected position increases, the value approaches 0. The change of the value becomes small after the number of the selected position became three. Therefore, selected first three positions become the optimal measurement positions. Fig.6 (a) - (c) show the experiment results. As for subject A, three channels, CH1, CH4 and CH8 were selected (cf. Fig.6(a)). As for subject B, three channels, CH1, CH3 and CH6 were selected (cf. Fig.6(b)). As for subject C, three channels, CH2, CH3 and CH7 were selected (cf. Fig.6(c)). Each optimal measurement positions were different though all subjects were healthy people. It is thought that the selected optimal measurement positions are related to the individual physical characteristics of the myoelectric signals by "the habit of a muscular usage" and "the physique", etc. Therefore, the proposed method can correspond to the individual situation of the remaining muscle of amputees.

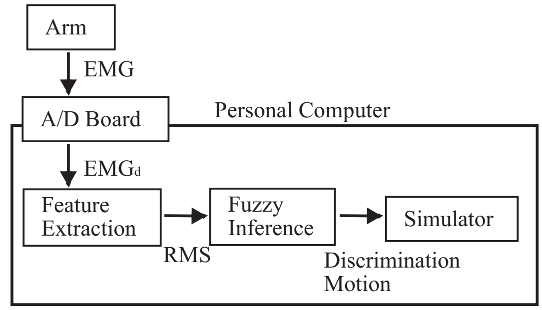


Fig. 7. Configuration of the motion discrimination system process.

III. MOTION DISCRIMINATION SYSTEM BY PATTERN ANALYSIS

A. Summary

This chapter confirms whether the forearm motions can be identified in the high precision from the myoelectric potential measured from the selected optimal positions. In the past, a lot of motion discrimination methods have been researched [1]-[18]. This study realizes the motion discrimination by the fuzzy inference method [5]. The motion discrimination is performed from the myoelectric potential measured from "the optimal position" and "the normal position", and the discrimination precision is compared. As for the number of the myoelectric sensors, the optimal position is three and the normal position is four. The configuration of the motion discrimination system process appears in Fig.7. This study outputs the discrimination motion to the simulator made by Open-GL.

B. Membership Function by Average Value and Standard Deviation of Myoelectric Potential

The membership function is designed by the average value (AVE) and the standard deviation (SD) from RMS

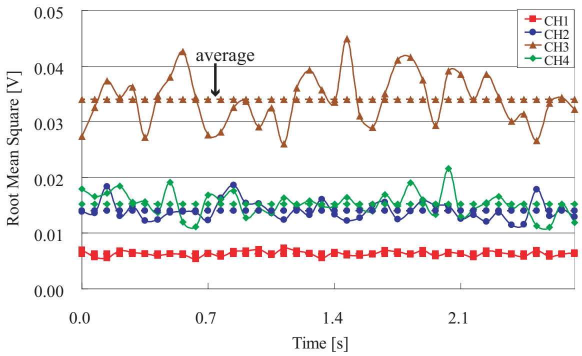


Fig. 8. Example of RMS waveform.

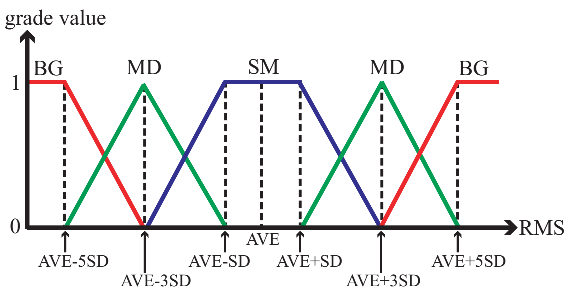


Fig. 9. Fuzzy membership function.

of the myoelectric potential for t times of each motion measured beforehand. Fig.8 shows the waveform of the myoelectric potential when maintaining the strength with a palm opened (the full line). The dash line shows AVE. The measured myoelectric potential never maintains a constant value when the muscle is having power maintained in the same way. Therefore this study obtains AVE and SD from RMS of t times of the identification target motion. This study assumes the distribution of RMS from AVE to be a normal distribution. And, the membership function is designed from a relation of AVE and SD in a normal distribution.

Therefore the membership function is designed as shown in Fig.9. If RMS is near to AVE, the membership function is SM (Small). If RMS is slightly far from AVE, the membership function is MD (Middle). If RMS is far from AVE, the membership function is BG (Big). The membership function takes the grade value from 0 to 1 depending on RMS. Such a membership function is designed for every channel of each motion.

C. Fuzzy Rule

The fuzzy rules are designed as shown in Table I. This table shows the motion discrimination method of the four channel estimation. This study determines the motion probability by the combination of SM, MD and BG of four channels. The motion probability is high probability (HP) in the case of SM on all channels, and middle probability (MP) in the case of SM on three channel and MD on one channel, and low probability (LP) in the case of SM on two channel and MD on two channels, and extremely-low probability (EP) in the case of SM on one channel and MD on three channels. In addition, the motion is not performed (No Motion : NM) in the case of BG on all channels. "Output value" of Table I shows the inference output value of each rule. When the number of the myoelectric sensors used is three, the row of "CH4" in Table I is omitted.

TABLE I
FUZZY IF-THEN CONTROL RULES.

	CH1	CH2	CH3	CH4	output value
HP	SM	SM	SM	SM	1.00
MP	MD	SM	SM	SM	0.75
MP	SM	MD	SM	SM	0.75
MP	SM	SM	MD	SM	0.75
MP	SM	SM	SM	MD	0.75
LP	SM	SM	MD	MD	0.50
LP	SM	MD	SM	MD	0.50
LP	MD	SM	SM	MD	0.50
LP	SM	MD	MD	SM	0.50
LP	MD	SM	MD	SM	0.50
LP	MD	MD	SM	SM	0.50
EP	SM	MD	MD	MD	0.25
EP	MD	SM	MD	MD	0.25
EP	MD	MD	SM	MD	0.25
EP	MD	MD	MD	SM	0.25
NM	BG	BG	BG	BG	0.00

This study applies the possibility distribution inference method [24]. The possibility distribution inference method has little computational complexity compared with the "Min-Max" method. The degree of confidence ω^k of each rule is calculated from Eq.(4). $A_p^k(x_p)$ is an output value of the membership function of each rule. x_p is an input value to each membership function. P is the number of parameters in the rule.

$$\omega^k = \prod_{p=1}^{P} A_p^k(x_p) \tag{4}$$

The inference result $\hat{y}$ of the entire rules is calculated from Eq.(5). $\hat{y}^k$ is the output value of each rule (cf. "output value" of Table I). K is the number of rules and K=16 in this study as shown in Table I. The inference result $\hat{y}$ is assumed to be the discrimination probability DP of motion. These inferences are performed for the each identification target motion.

$$\hat{y} = \frac{\sum_{k=1}^{K} \omega^k \cdot \hat{y}^k}{\sum_{k=1}^{K} \omega^k} \tag{5}$$

IV. MOTION DISCRIMINATION EXPERIMENT

A. Experiment Environment

Fig.10 shows the experimental setup of motion discrimination and Fig.11 shows the simulator. In this study, six types of motion, "Open", "Grasp", "Flexion", "Dorsiflexion", "Pronation" and "Supination" are applied as the identification target motions (cf. Fig.12). In addition, the motion is recognized when the discrimination probability DP is more than

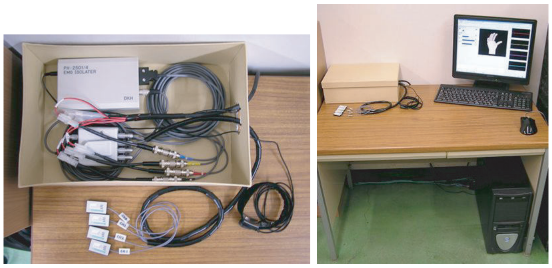


Fig. 10. Experimental setup of motion discrimination.

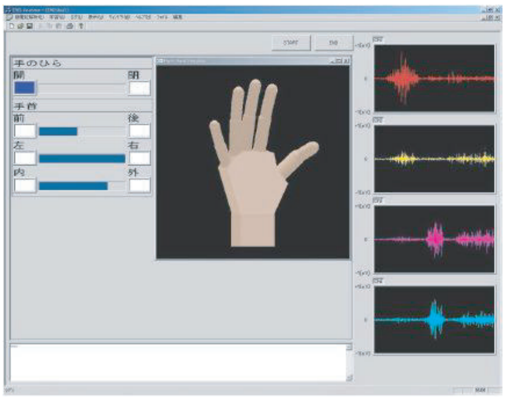


Fig. 11. Waveform drawing application and myoelectric hand simulator.

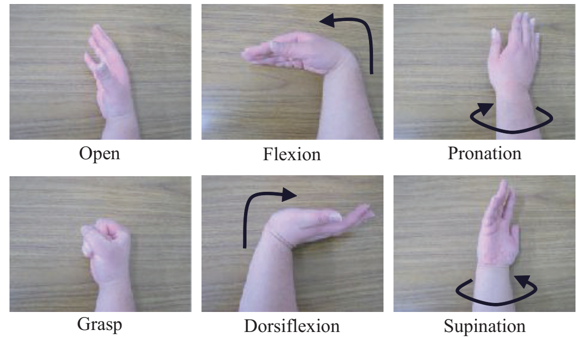


Fig. 12. Six types of motions are applied as the identification target motions.

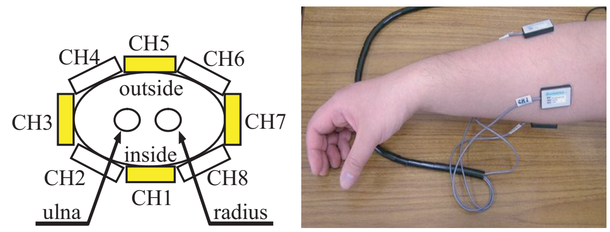


Fig. 13. Normal measurement positions (CH.1,3,5,7) of the myoelectric sensors of four channels are assigned every 90 degrees.

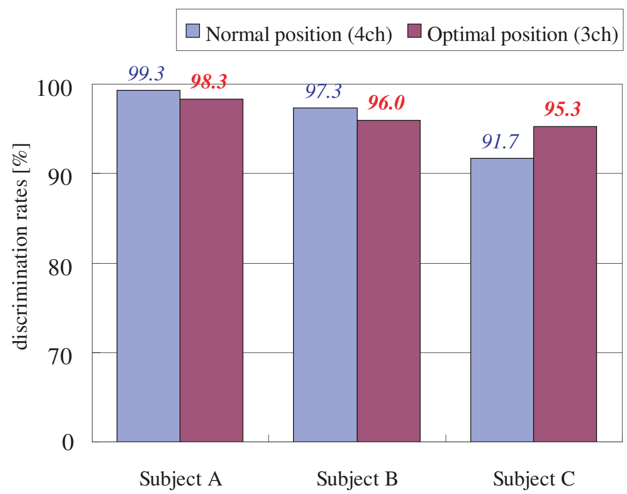


Fig. 14. Discrimination experimental results.

"0.8" and the recognition is canceled if the discrimination probability *DP* becomes below "0.3".

In these experiment contents, six kinds of motions are performed by 50 times respectively. The discrimination result by the fuzzy inference identifies the probability that the result is correct for the real motion. This study applies on the selected optimal measurement positions and the normal measurement positions and compares the discrimination precision. The normal measurement positions of the myoelectric sensors of four channels are assigned every 90 degrees to the forearm of the subject (cf. Fig.13). This measurement position set has been often used in the past studies of the motion discrimination based on the myoelectric signal. These experiments never give an arm load and three subjects (A, B, C) are the same as the optimal position estimation experiments in the last chapter.

B. Experiment Results

Fig.14 shows the experiment results. All motions were able to obtain the high discrimination precision more than 90% for three subjects and all subjects were able to obtain the high discrimination precision by measuring the myoelectric potential at each optimal positions. In addition, as for subject C, the discrimination rates by three myoelectric sensors at the optimal positions was higher. It is thought that the position of the cause of the misrecognition can be avoided by estimating the optimal positions.

In addition, the discrimination rate by three myoelectric sensors at the optimal positions was almost at the same level as the rate by four myoelectric sensors at the normal positions. Therefore these experiments verified that the number of myoelectric sensors could be reduced by measuring the myoelectric signals at the optimal positions.

C. Discussion

This study realized the human forearm motion discrimination with only three myoelectric sensors by measuring the myoelectric signal at the optimal measurement positions but still has the following important future problems.

- This study was able to obtain the high discrimination precision with only three myoelectric sensors. When the myoelectric hand is used, fewer myoelectric sensors are more practical. In the future, the motions will have to be identified with fewer myoelectric sensors. Therefore the optimal measurement positions will have to be estimated from the myoelectric signals measured at multiple and precise positions by increasing the number of myoelectric sensors.

- This study was able to correspond to the individual physical characteristics, "the habit of a muscular usage" and "the physique", etc. in healthy people. Therefore there is a possibility that the proposed method will show the ability also for forearm amputees. However the myoelectric signal characteristics might be different between forearm amputees and healthy people. Some experiments will have to be performed by real amputees.
- The kinds of the identification target motions will have to be increased and the motions will have to be combined so that the discrimination system can respond to the various motions and the situations of the activities of daily living (ADL).

V. CONCLUSION

This paper describes an optimal measurement position estimation by the discriminant analysis based on Wilks' lambda for the myoelectric hand control. This study was able to obtain the high discrimination precision with only three myoelectric sensors by measuring the myoelectric signals at the optimal measurement positions. The optimal measurement positions for the motion discrimination are different according to the remaining muscle situation of amputees. It is probable that the proposed method will show the ability also for real amputees. Therefore this study is very useful when real amputees use myoelectric hands.

The motion misrecognition is very dangerous for the myoelectric hand control. Therefore it is necessary to get the high discrimination precision. Our future work will solve some important problems described in the last chapter.

REFERENCES

[1] A. Hiraiwa, N. Uchida, K. Shimohara, and N. Sone, "EMG Recognition with a Neural Network Model for Cyber Finger Control", *Trans. of SICE*, vol. 30, No. 2, pp. 216-224, 1994.

[2] T. Tsuji, D. Mori, and K. Ito, "Motion Discrimination Method from EMG Signals Using Statistically Structured Neural Networks", *IEEJ Trans. EIS*, vol. 112, No. 8, pp. 465-473, 1992.

[3] O. Hukuda, N. Bu, and T. Tsuji, "Control of an Externally Powered Prosthetic Forearm Using Raw-EMG Signals", *Trans. of SICE*, vol. 40, No. 11, pp. 1124-1131, 2004.

[4] A. Kiso, H. Seki, H. Minakata, and S. Tadakuma, "Human Forearm Motion Discrimination by Concise Neural Network for Myoelectric Hand Control", *Journal of the Society of Life Support Technology*, vol. 21, No. 2, pp. 12-19, 2009.

[5] A. Kiso, and H. Seki, "Robust Motion Discrimination Based on Human Forearm Myoelectric Potential by Adaptive Fuzzy Inference Considering Muscle Fatigue", in *Proc. IEEE EMBS 31st Annu. Int. Conf.*, pp. 2991-2995, 2009.

[6] I. Kajitani, T. Higuchi, and N. Otsu, "Improvements to action decision rates in myoelectric-controlled multi-functional hand", *Trans. of Human Interface Society*, vol. 5, No. 4, pp. 421-428, 2003.

[7] K. Nagata, K. Andou, M. Yamada, and K. Magatani, "Recognition of Hand Motions Based on Multi-channel SEMG Employing the Monte Carlo Method for Channel Selection", *Trans. of Japanese Society for Medical and Biological Engineering*, vol. 44, No. 1, pp. 138-147, 2006.

[8] H. Sakakihara, "Development of Myoelectrically-controlled Below-elbow Prosthesis with Wrist Rotation Function", *IEICE Technical Report*, vol. 107, No. 154, pp. 67-70, 2007.

[9] Jun-Uk Chu, and Yun-Jung Lee, "Conjugate-Prior-Penalized Learning of Gaussian Mixture Models for Multifunction Myoelectric Hand Control", *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 17, No. 3, pp. 287-297, 2009.

[10] J. Chiang, Z. J. Wang, and M. J. McKeown, "A Hidden Markov, Multivariate Autoregressive (HMM-mAR) Network Framework for Analysis of Surface EMG (sEMG) Data", *IEEE Trans. Signal Process.*, vol. 56, No. 8, pp. 4069-4081, 2008.

[11] A. D. C. 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, 2005.

[12] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control", *IEEE Trans. Biomed. Eng.*, vol. 40, No. 1, pp. 82-94, 1993.

[13] F. H. Y. Chan, Yong-Sheng Yang, F. K. Lam, Yuan-Ting Zhang, and P. A. Parker, "Fuzzy EMG classification for prosthesis control", *IEEE Trans. Rehabil. Eng.*, vol. 8, No. 3, pp. 305-311, 2000.

[14] B. Karlik, M. O. Tokhi, and M. Alci, "A fuzzy clustering neural network architecture for multifunction upper-limb prosthesis", *IEEE Trans. Biomed. Eng.*, vol. 50, No. 11, pp. 1255-1261, 2003.

[15] A. B. Ajiboye, and R. F. ff. Weir, "A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control", *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, No. 3, pp. 280-291, 2005.

[16] Rami N. Khushaba, Ahmed Al-Ani, and Adel Al-Jumaily, "Orthogonal Fuzzy Neighborhood Discriminant Analysis for Multifunction Myoelectric Hand Control", *IEEE Trans. Biomed. Eng.*, vol. 57, No. 6, pp. 1410-1419, 2010.

[17] K. Englehart, and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control", *IEEE Trans. Biomed. Eng.*, vol. 50, No. 7, pp. 848-854, 2003.

[18] Jun-Uk Chu, I. Moon, Yun-Jung Lee, Shin-Ki Kim, and Mu-Seong Mun, "A supervised feature-projection-based real-time EMG pattern recognition for multifunction myoelectric hand control", *IEEE Trans. Mechatronics*, vol. 12, No. 3, pp. 282-290, 2007.

[19] T. Shibanoki, K. Shima, T. Tsuji, T. Takaki, A. Otsuka and T. Chin, "A Novel Variable Selection Method Based on a Partial KL Information Measure and Its Application", *Trans. of SICE*, vol. 45, No. 12, pp. 724-730, 2009.

[20] K. Nishihara, H. Kawai, T. Gomi, M. Terajima, and Y. Chiba, "Investigation of Optimum Electrode Locations by Using an Automatized Surface Electromyography Analysis Technique", *IEEE Trans. Biomed. Eng.*, vol. 55, No. 2, pp. 636-642, 2008.

[21] H. Huang, P. Zhou, G. Li, and T. A. Kuiken, "An Analysis of EMG Electrode Configuration for Targeted Muscle Reinnervation Based Neural Machine Interface", *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, No. 1, pp. 37-45, 2008.

[22] C.J. De Luca and E.J. van Dyk, "Derivation of some parameters of myoelectric signals recorded during sustained constant force isometric contractions", *Biophysical Journal*, vol. 15, No. 12, pp. 1167-1180, 1975.

[23] L. Li and B. Baum, "Electromechanical delay estimated by using electromyography during cycling at different pedaling frequencies", *Journal of Electromyography and Kinesiology*, vol. 14, No. 6, pp. 647-652, 2004.

[24] Y. Nakamori and M. Ryoke, "Identification of Fuzzy Prediction Models Through Hyperellipsoidal Clustering", *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-24, No. 8, pp. 1153-1173, 1994.