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Robust Motion Discrimination Based on Human Forearm Myoelectric Potential by Adaptive Fuzzy Inference Considering Muscle Fatigue

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***Abstract*— This paper describes a robust motion discrimination method based on the myoelectric potential of human forearm by the adaptive fuzzy inference considering the muscle fatigue. In the conventional studies, a motion discrimination based on the myoelectric potential of human forearm realizes the high discrimination precision. However, the characteristic of the myoelectric potential gradually changes for muscle fatigue. Therefore the motion discrimination considering muscle fatigue is required. The purpose of this study is to correspond to the change in the myoelectric potential by the muscle fatigue and keep the high discrimination precision. This study proposes the redesign method of the fuzzy inference adapting to the dynamic change of the myoelectric potential by the muscle fatigue. Some experiments on the myoelectric hand simulator show the effectiveness of the proposed motion discrimination method.**

I. INTRODUCTION

In the modern society where the safe management and accident prevention are recognized enough, there is a person losing his/her arm by a traffic accident or a disaster. Therefore the development of artificial arm having a same function for lost arm is expected. An electromyogram (EMG) is always paid its attention to the control signal of such an artificial arm, and many studies and development are performed.

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

In the conventional study, some methods such as the motion discrimination by the backpropagation based on frequency information of the myoelectric potential [1], the motion discrimination by the neural network based on statistics structure [2], the motion discrimination by "reconfiguration possibility hardware and the genetic algorithm" [3], the motion discrimination by the channel choice with the monte carlo method by the electrode of 6*16 channels [4], the movement identification by "fast Fourier transform and chief ingredient analysis and the neural network" [5] have been used. In the other studies, the hidden Markov model [7], [8], the neural network [9], the fuzzy inference [10]-[12], the linear discriminant analysis (LDA) [13], [14] have been used.

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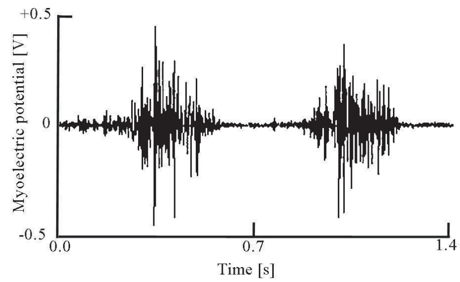

Fig. 1. Myoelectric potential waveform example.

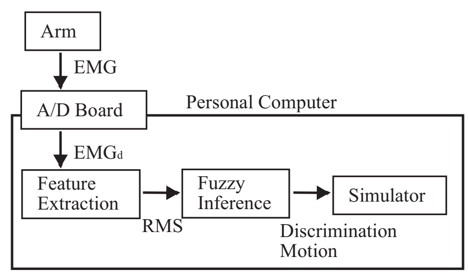

Fig. 2. System schema.

This study uses the fuzzy inference for the motion discrimination based on the myoelectric potential signal of the forearm. Because the fuzzy inference does not cause the problem such as the local minimum of the neural network and the fuzzy inference is easy to perform the redesign for corresponding to change of the myoelectric potential by the muscle fatigue, this study uses the fuzzy inference. The characteristic of the myoelectric potential gradually changes for muscle fatigue [15]. Therefore the motion discrimination considering muscle fatigue is required [16]. The purpose of this study is to correspond to the change in the myoelectric potential by the muscle fatigue and keep the high discrimination precision. This study proposes the redesign method of the fuzzy inference adapting to the dynamic change of the myoelectric potential by the muscle fatigue. Some experiments on the myoelectric hand simulator show the effectiveness of the proposed motion discrimination method.

II. MOTION DISCRIMINATION SYSTEM

A. Summary

A flow of the motion discrimination system process appears in Fig.2. This study outputs the discrimination motion to the simulator made by using Open-GL.

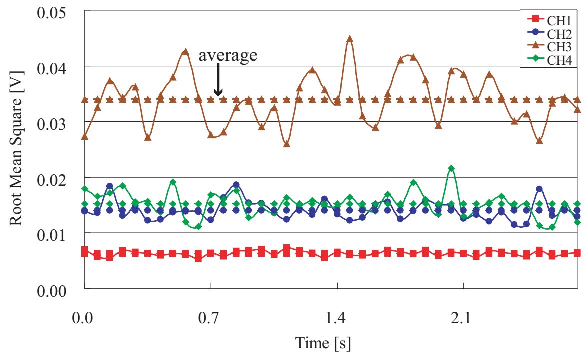

Fig. 3. RMS waveform example.

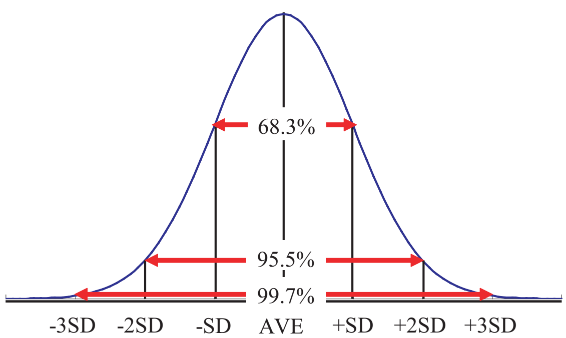

Fig. 4. Normal Distribution.

B. Measurement of Myoelectric Potential

The measurement of the myoelectric potential uses a dry process myoelectric amplifier SX230 made in Biometrics Company of four channels. The amplification rate is 1000 times, and the bandwidth is 20Hz - 460Hz. This myoelectric amplifier 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 (cf. Fig.7).

C. Feature Extraction

This study uses the root mean square (RMS) that shows the power of a signal for the feature quantity. The frequency information is often used to the feature quantity, but RMS is used for the feature quantity because the calculation of the frequency information needs much calculation amount. The RMS is defined as

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

The symbol *e(t)* is the myoelectric potential signal, and $-T,+T$ is a calculation interval. This study assumes the calculation interval 70[ms].

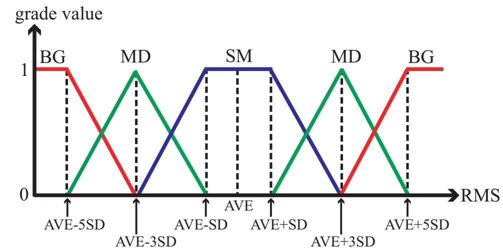

Fig. 5. Fuzzy membership function.

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

III. MOTION DISCRIMINATION BY FUZZY INFERENCE

A. 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 of the myoelectric potential for t times of each motion measured beforehand. Fig.3 shows the waveform of the myoelectric potential when maintaining strength with a palm opened (the full line). The dash line shows the average value. The measured myoelectric potential never maintains a constant value when the muscle is having power maintained in the same way. Therefore this study obtains the average value and the standard deviation from RMS of t times of the identification target motion. The distribution that varies from this average value is regarded as a normal distribution. Based on the normal distribution, there are data of 68.3% in the range of ±SD from AVE, and there are data of 95.5% in the range of ±2SD from AVE, and there are data of 99.7% in the range of ±3SD from AVE (cf. Fig.4).

Therefore, the membership function is designed as shown in Fig.5. 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 grade value from 0 to 1 depending on RMS. Such a membership function is designed for every channel of each motion.

B. Fuzzy Rule

The fuzzy rules are designed as shown in Table I. This study decides the motion probability by a 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.

The proposed fuzzy inference method applies the possibility distribution inference method [17]. 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 (2). $A_p^k(x_p)$ 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.

$$\omega^k = \prod_{p=1}^{P} A_p^k(x_p) \tag{2}$$

The inference result $\hat{y}$ of the entire rule is calculated from (3). $\hat{y}^k$ are an output value of each rule (cf. "output value" of Table I). K is the number of rules, this study is K=16 by 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 object motion.

$$\hat{y} = \frac{\sum_{k=1}^{K} \omega^k \cdot \hat{y}^k}{\sum_{k=1}^{K} \omega^k} \tag{3}$$

IV. ROBUST DISCRIMINATION FOR MUSCLE FATIGUE

The myoelectric potential gradually changes according to muscle fatigue, and the motion discrimination considering muscle fatigue is required. Therefore this study tries to realize the redesign of fuzzy inference system corresponding to the change of the myoelectric potential. However the discrimination system does not understand the motion that the subject is intending. In this study, if the same motion is continuously discriminated L times, it is assumed that the discrimination result is correct. The average value and the standard deviation for the redesign are calculated from "the calculation data of the latest average value and standard deviation" and "the L th RMS of the myoelectric potential". The membership function is redesigned by the average value and the standard deviation of the redesign data. The discrimination number of times is recounted after the redesign, and the average value and the standard deviation are sequentially updated.

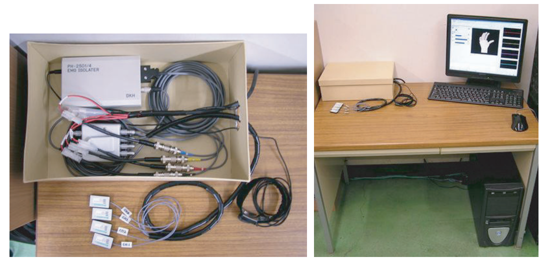

Fig. 6. Experimental setup of motion discrimination.

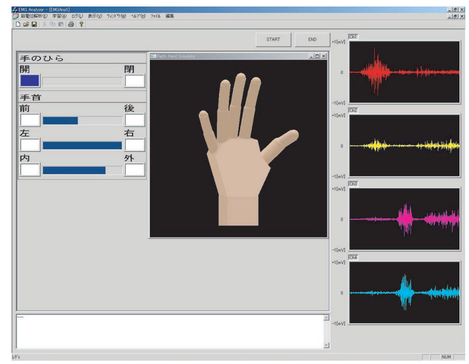

Fig. 7. Waveform drawing application and myoelectric hand simulator.

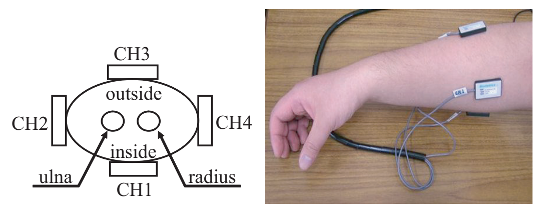

Fig. 8. Measurement position of myoelectric potential.

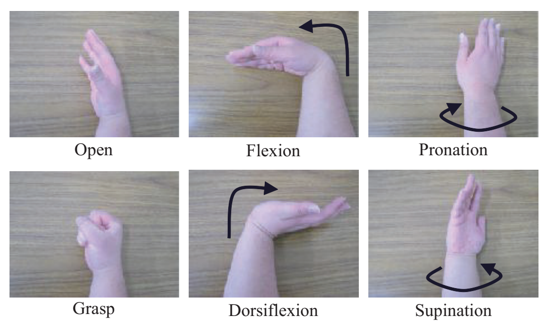

Fig. 9. Discrimination Motion.

V. MOTION DISCRIMINATION EXPERIMENT

A. Experiment Environment

Fig.6 shows the experimental setup of motion discrimination and Fig.7 shows the simulator. The measurement position allocates the myoelectric amplifier of four channels every 90 degrees to the right forearm of the subject (cf. Fig.8). Because there are "flexor digitorum muscle", "flexor carpi radialis muscle" and "flexor carpi ulnaris muscle", etc. used for the identification target motions at this position, the myoelectric potential is measured at this position. In this

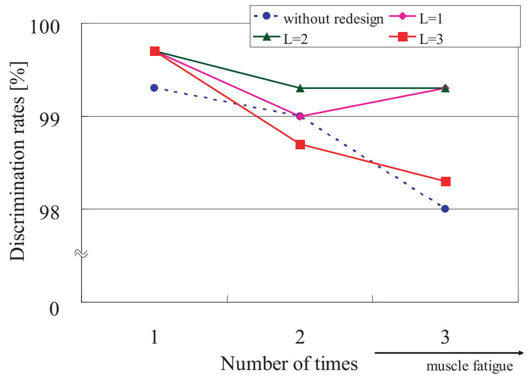

Fig. 10. Experimental results "with and without redesign" (Subject A).

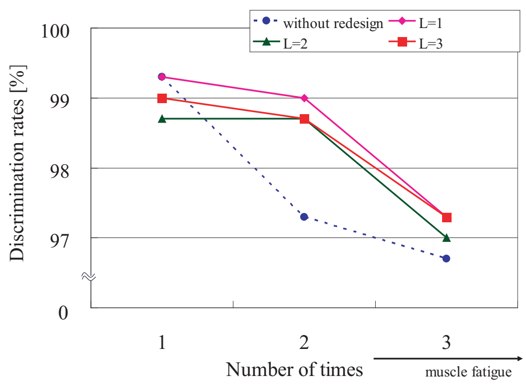

Fig. 11. Experimental results "with and without redesign" (Subject B).

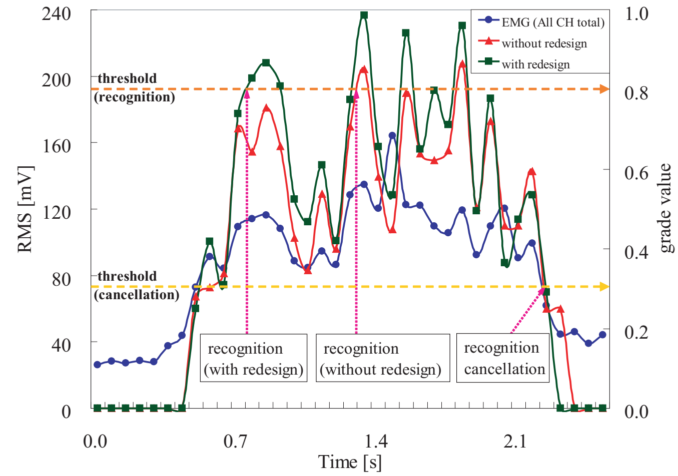

Fig. 12. Fuzzy Inference Result with and without redesign.

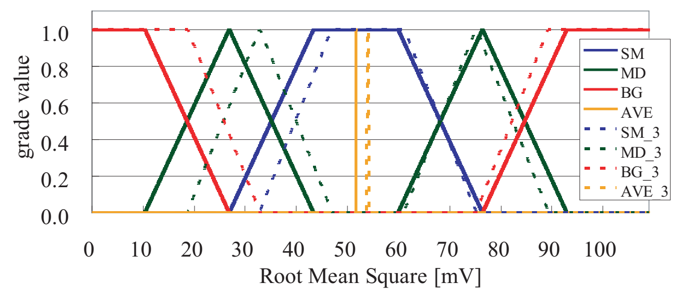

Fig. 13. Change of Membership by redesign.

study, six kinds of motions of "Open", "Grasp", "Flexion", "Dorsiflexion", "Pronation" and "Supination" are applied as the identification target motions (cf. Fig.9). In addition, the motion is recognized when the discrimination probability *DP* is more than "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 real motion. This study continuously performs these experiments 3 times without resting the arm, and the change of the discrimination precision is confirmed. The condition of the redesign is assumed to be L=1$\sim$3 time. These experiments never give an arm load, and it is performed with two physically unimpaired people (subject A, B).

B. Experiment Results

Fig.10 and Fig.11 show the experiment results. All motions were able to get the high discrimination precision more than 90% with two subjects. Both the redesigns (with and without) were almost the same as the identification rate, but the recognition at the beginning of the motion was occasionally delayed without the redesign. An example of delay of the motion discrimination when grasping a palm is shown in Fig.12. It shows "the total value of all channels of the myoelectric potential" and "the result of the fuzzy inference by the redesign (with and without)". The grade values with redesign are totally higher than those without redesign. This result shows that the proposed redesign system realizes the higher performance of motion inference. Because the result of the fuzzy inference deteriorates without the redesign as shown in Fig.12, the motion recognition is late. Therefore, the user is made to feel the delay. The result of a fuzzy inference is improved by the redesign. It is possible to correspond to the change in the myoelectric potential by the redesign. Consequently, the delay at the beginning of recognition was able to be suppressed by the redesign.

Fig.13 shows the change in the membership function by the redesign. The full line shows the membership function before experiments, and the dash line shows the membership function after the third experiment. The membership function has been changed according to the change of the myoelectric potential by the muscle fatigue.

C. Discussion

This study realized a human forearm motion discrimination based on the myoelectric signal by the fuzzy inference but still has the following important future problems.

- This study set the threshold of the discrimination probability *DP* of the motion with a fixed value, but the same fixed value may not be the optimal value to all motions. Therefore, the threshold of the discrimination probability *DP* has to be designed as the optimal value.

- There is a possibility of influencing the discrimination precision after lost of fatigue when the redesign is made to correspond to the muscle fatigue completely. Therefore, the redesign has to be designed as the optimal number of times.
- 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).
- The myoelectric potential signal is different from between an amputee and a physically unimpaired person. Therefore some experiments will have to be performed by amputees.

VI. CONCLUSION

This paper proposed a robust motion discrimination method based on the myoelectric potential of human forearm by the adaptive fuzzy inference considering the muscle fatigue. This study was able to obtain the high discrimination precision by the redesign of the fuzzy inference adapting to the dynamic change of the myoelectric potential by the muscle fatigue. In addition, the delay of the recognition beginning was able to be suppressed by the redesign. The misrecognition of the motion is very dangerous to the myoelectric hand control. Therefore it is necessary to get high discrimination precision. Our future work will solve some important problems described in the last chapter.

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