EMG PATTERN CLASSIFICATION FOR A PROSTHETIC FOREARM WITH THREE DEGREES OF FREEDOM

Koji ITO*, Toshio TSUJI**, Atsuo KATO*** and Masami ITO****

* Toyohashi University of Technology, Toyohashi, 441, JAPAN
** Faculty of Engineering, Hiroshima University, Higashi-Hiroshima, 724, JAPAN
*** Aichi Institute of Technology, Toyota, 470-03, JAPAN
**** Faculty of Engineering, Nagoya University, Nagoya, 464-01, JAPAN

ABSTRACT : We developed an EMG controlled prosthetic forearm with three degrees of freedom actuated by small size ultrasonic motors. Its weight is less than 700 g and the size is the same as the adult's forearm. The interface between the amputee and the prosthetic forearm was designed on the basis of the fact that the amputee still preserves the phantom limb motor map after amputation.

The present paper proposes a method to estimate the motion intended by an amputee from the EMG signals using neural network. The method presented here can discriminate the amputee's intended motion among six kinds of limb-functions from the multi-channel EMG signals preprocessed by the bandpass and smoothing filters. The cross-information among the EMG signals can be utilized to make the electrode locations flexible, and the band-pass filters can provide the amplitude and frequency characteristics of the EMG signals. The experiments of three subjects and four electrode locations demonstrates that the method can discriminate six motions of forearm and hand from unlearned EMG signals with the accuracy above 90 %.

I. INTRODUCTION

Since the 1950's, many research and development efforts on EMG contolled artificial arms have been done. The representative prosthetic arms are Russian hand, Boston arm, Otto Bock, Utah arm, and WIME hand. Within these artificial arms, EMG controlled electric hands are actually fitted. One of the reasons for the success of the electric hands lies with the controllability. However, it never satisfies the amputee when compared with the natural hand. Because the conventional hands are limited to only one or two degrees of freedom. And they make acoustically noises due to the high speed of motor revolutions.

we developed an EMG controlled forearm with three degrees of freedom using small size ultrasonic motors. The ultrasonic motors were used to realize all six motions in the forearm. If the electric DC motors are used, it is impossible to realize six motions. Also, the arm is acoustically quiet, because the speed of motor revolution is very lower comparing with the DC motor.

The present paper discusses a method to estimate the motion intended by an amputee from the EMG signals using neural network. Though several methods have already been reported on the motion discrimination using the EMG signal, almost of them relate the EMG data to stochastic sequences by linear difference equations(e.g. AR model)[1)-5)]. However, different muscles work and signal sources and paths to the recording electrode change depending on the kind of motion. Therefore, the properties of the surface EMG vary nonlinearly with changing limb function. In addition, since the model parameters are fixed, it is impossible to be adapted to gradual changes of EMG properties resulting from muscle fatigue, sweating and the change of electrode characteristics.

In this paper, we propose a method which can discriminate the amputee's intended motion among six kinds of limb-functions using the multichannel EMG signals preprocessed by the band-pass and smoothing filters. The cross-information among the EMG signals can be utilized to make the electrode locations flexible, and the band-pass filters can provide the amplitude and frequency characteristics of the EMG signals. It is shown that after several tens of training iterations, 90 % correct classification level is achieved. Then the method proposed is applied to control of a prosthetic forearm with three degrees of freedom.

II. PROSTHETIC FOREARM USING ULTRASONIC MOTOR

The prosthetic forearm which was developed on an experimental basis is shown in Fig.1. It is driven by

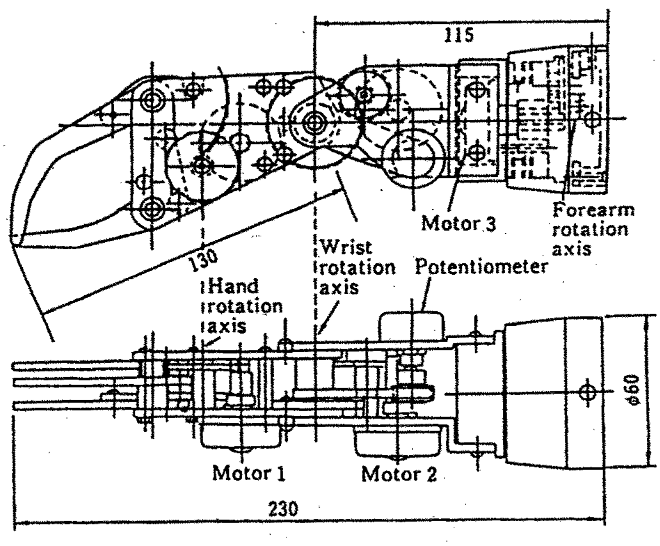

Fig.1 Prosthetic forearm with three degrees of freedom.

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Table 1 Specifications of the prosthetic forearm with three degrees of freedom

	Motions	Movable range (the time required)	Holding force	Gear ratio
Forearm	Pronation supination	162° (0.6~30 s)	1.71 kg·cm	4.5
Wrist	Flection extention	135° (1.1~20 s)	10.40 kg·cm	17.5
Hand	Grasping opening	125 mm (1.1~50 s)	4.16 kg	29.8

ultrasonic motors installed in the forearm, wrist and hand, and has three degrees of freedom, i.e., six motions of wrist flection and extension, forearm pronation and supination, and hand grasping and opening. Table 1 shows the specifications of the powered prosthetic forearm. The total length is 245 mm, the weight is 690 g and the grasping force is 4.16 Kg. The gear ratio is much less as compared with DC motor actuator.

III. AMPUTEE-PROSTHESIS INTERFACE

The block diagram of the amputee- prosthesis interface for controlling the forearm is shown in Fig.2. The surface EMG is measured from a part of the muscles which have actuated the original limb, and the motion intended by the amputee, such as flection, extension, pronation, supination, grasping and hand-opening, is estimated. In parallel, the muscle force is estimated from the EMG signals. Then the signal to drive and control the prosthesis is produced from both. In the following, the discrimination and force identification procedures are described.

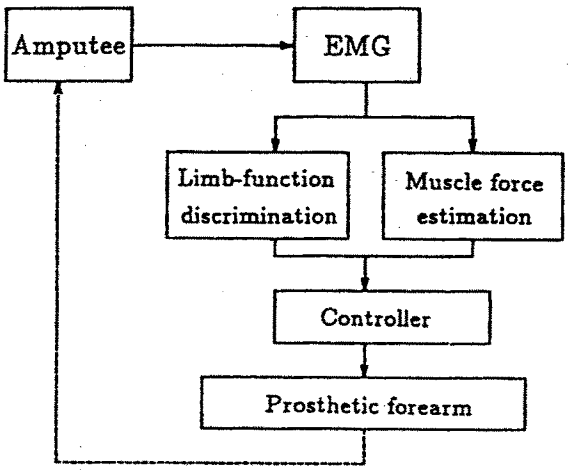

Fig.2 Amputee-prosthesis interface.

IV. LIMB-FUNCTION DISCRIMINATION BY NEURAL NETWORK

The flow chart of the limb-function discrimination procedure proposed here is shown in Fig.3, which is composed of band-pass filters, rectification, smoothing filters and neural network.

A. Band-pass filter

The raw EMG signals measured at the surface of the amputee's skin are passed through the band-pass FIR filters. Then each of the L channels EMG signals is divided into N band frequency components as follows.

$$y_{ij}(t) = \sum_{k=0}^{k} h_j(k)\, x_i(t-k) \qquad (1)$$

where $x_i(t)$ is the raw EMG signal (i=1,2,..L : L is number of electrodes), $h_j(k)$ is the impulse response of the j th band-pass filter (j=1,2,...,N) and $y_{ij}(t)$ is the output of the j th band-pass filter with the EMG $x_i(t)$.

B. Rectification and Smoothing

The N×L EMG signals obtained from the band-pass filters are rectified and passed through individual one-pole Butterworth filters each with a low pass cutoff frequency of 1 Hz. The time-averages Z_{ij} of the resulting EMG signals $Y_{ij}(t)$ (i=1,2,...,L ; j=1,2,...,N) are computed by

$$Z_{ij} = \sum_{t=1}^{T} Y_{ij}(t)/T. \qquad (2)$$

Further Z_{ij} is normalized by

$$S_{ij} = Z_{ij} / \sum_{i=1}^{L} Z_{ij}. \qquad (3)$$

where $\sum_{i=1}^{L} S_{ij} = 1.$

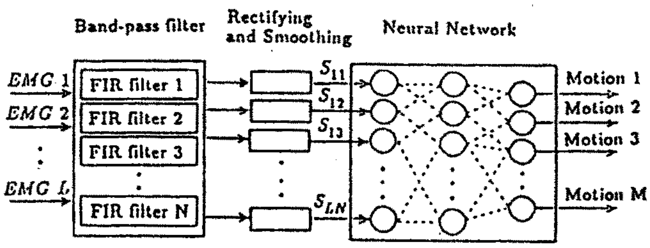

Fig.3 A limb-function discrimination method using neural network.

C. Neural Network Subsystem

A feedforward type neural network is used to classify the rectified and smoothed EMG signals[6]. The neural network consists of an input layer of L× N units, a hidden layer of ten units, and a output layer of M units. Each unit of the output layer represents one of M kinds of motions.

The input ui and output oi of the unit i are defined as follows.

$$u_i = \begin{cases} I_i & \text{(input layer units)} \\ \sum_j W_{ij}\, o_j & \text{(hidden and output layer units)} \end{cases} \quad (4)$$

$$o_i = f_i(u_i) \quad (5)$$

where the input I_i to the input layer units is S_{ij} of Eq.(3). The input to each unit of the hidden and output layers is a summation of all the individual weighted outputs passed from the previous layer. The output of each unit is then a function of the summation of these inputs. The output function has the following form,

$$f_i(u_i) = \begin{cases} u_i & \text{(input layer units)} \\ 1/(1 + e^{-u_j}) & \text{(hidden and output layer units)} \end{cases} \quad (6)$$

D. Network Pretraining

After attaching the prosthetic forearm, the amputee is asked to perform each of M kinds of motions by n times. Then M× n EMG data are acquired. The neural network is trained by error back propagation algorithm using these M × n data. Then for motion i, the network weights are updated such that unit i of the output layer gives 1.1 and all units except unit i give -0.1. Why 1.1 and -0.1 are used as the desired outputs is to prompt the convergence of the network learning. The learning process is finished when the value of the corresponding unit of the output layer became more than 0.8 and the values of units other than it became less than 0.2 for each motion. Further the initial values of the network weights are uniform random numbers such that $|W_{ij}| < 1.0$.

E. Function Discrimination

It is assumed that the amputee intends to make one of M motions. Then the EMG signals are measured and inputted into the system.

Since each unit of the output layer has the sigmoidal function, the output value is within 0 and 1. When one of the units of the output layer is more than 0.5 and all the others are less than 0.3, it is concluded that the motion assigned to the unit with the value more than 0.5 is intended by the amputee. Unless these conditions are satisfied, the discrimination is left undetermined. This is to exclude uncertain discriminations and to evade wrong motions of the prosthetic arm. In addition, this makes possible to deal with the case when the amputee has intended to perform some motion except M kinds of motions

F. On Line Training

When the prosthetic arm is in daily use, it is necessary to consider the variations of EMG properties resulting from muscle fatigue, sweating and the change of electrode characteristics. Therefore, in order to use the prosthetic arm successively all day, it is required to find the discrimination method adaptable to these variations.

Now, let's consider to update the network weights even in use of the prosthetic arm. When using the prosthetic arm, however, we can not ascertain whether the estimated motion coincided with the amputee's intended one, i.e. we can not directly find the desired output (teacher's signal). Therefore, we propose a method which updates the weights based on the discrimination results with high output values as follows.

1) Find a set of the EMG pattern and the output motion which gave the output value more than 0.6 during use of the prosthetic arm, and add it to the teacher's signals. Then delete the oldest one of the stored teacher's signals (M× n patterns).
2) Update the network weights using new teacher's signals.
3) In the case where the learning is not finished within five times, the weights are not updated to avoid the wrong learning.

V. PROSTHETIC FOREARM CONTROL

A. Basic Experiments

A basic experiment was performed to investigate the discrimination ability and the convergence of learning. The experimental conditions are as follows.

1) Motions : wrist flection and extension, forearm pronation and supination, and hand grasping and opening.
2) Subjects : Two adults(male, normal) and one adult (amputated at the forearm, 6 cm from the left wrist joint). The amputee and the normal A are right-handed, and the normal B is left-handed.
3) Sites of electrodes : Four pairs of surface electrodes(L=4) were attached on the forearm, 7 cm from the elbow joint. The electrode is dry-type made by Imasen Technical Lab. Three kinds of electrode arrangements are shown in Table 2. EMG signal in each channel was A/D converted with the sampling frequency of 1 KHz and were stored in the computer as the data file.
4) Training data : The amputee was asked to perform each of M kinds of motions by one time. Then the EMG signals for 2 sec after a transient period were measured. The band-pass filters were composed of three kinds(N=3) of central frequencies, 70 Hz, 160 Hz and 360 Hz with 40 Hz band width each. The order of FIR filter was K=10 and the impulse response $h_j(k)$ was computed by Remez's algorithm. Each of the

stored EMG data was divided into 10 data sets of 200 msec intervals. Based on ten data sets, S_{ij} ($i=1,..,4$; $j=1,2,3$) in (3) was computed ($T=100$ msec : $n=10$). These 6×10 data were used to train the neural networks. In addition, each of M kinds of motions were performed by 100 times separately from these data and the EMG signals were used to confirm the function discrimination after learning.

Table 2 represents number of learning iterations, success rates and undetermined rates in different experiment conditions, where the success rate is the ratio of the correct discriminations in discriminated trials and the undetermined rate is the ratio of the undetermined trials in all trials. They are averages over ten kinds of initial values of the network weights. Note that the success rates are more than 90% independently of subjects and electrode locations, and especially the numbers of iterations training the neural networks are less than 30.

Table 2 Electrode locations and motion discrimination rates.

Experiment	No.1	No.2	No.3	No.4	No.5
Subject	Normal A	Normal A	Normal B	Normal B	Amputee
Electrode locations					
Number of iterations	20.1	17.8	9.0	26.0	14.9
Success rates (%)	100.0	100.0	92.7	95.5	93.5
Undetermined rates (%)	3.4	5.7	8.7	12.0	13.4

Average values for 10 kinds of initial values of the synaptic weights

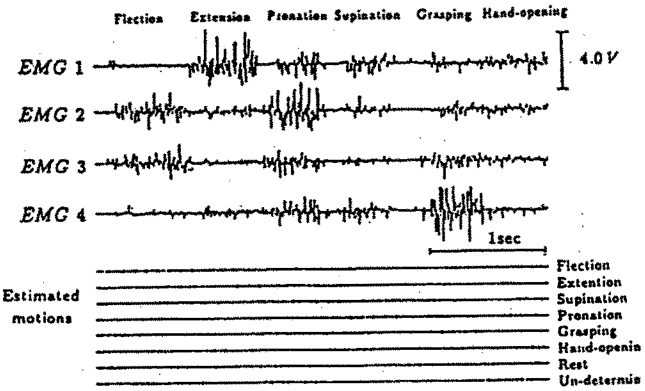

Fig.4 Discrimination results of a series of motion(amputee).

When the amputee performed M kinds of motions in consecutive order, the intended motions were estimated at 100 msec intervals and are shown in Fig.4. The above is four channels EMG patterns and the lower is the discriminated results(black dots). The horizontal lines denote wrist flection, wrist extension, forearm pronation, forearm supination, hand grasping, hand opening, rest and no action in a descending order. When the amplitudes of EMG signals are less than the threshold level, it was concluded that the amputee was at rest. Though the EMG signals during stationary periods give correct results, quite a number of wrong discriminations occurs particularly at the time of a change of motions. This is due to sharp fluctuations of the EMG patterns.

B. Prosthetic Forearm Control Experiment

A prosthetic forearm was controlled using the limb-function discrimination method in order to confirm the adaptation ability to the variation of the EMG patterns. The prosthetic forearm is driven by ultrasonic motors installed in the forearm, wrist and hand, and has three degrees of freedom, i.e., six motions of wrist flection, wrist extension, forearm pronation, forearm supination, hand grasping and hand opening. EMG data processing was done by using two CPU(Transputer, T800, 25MHz) in parallel. The time for training the neural networks was taken 763 msec/iteration, the time for the discrimination 2.4 msec, the time for A/D conversion, rectification, smoothing and D/A conversion 1 msec. The subject is normal and four pairs of surface electrodes were attached with 90-deg difference on the forearm. At first, the neural network was trained by off-line learning. Then the subject was asked to continue to perform six kinds of motions in no particular order for about one hour. During the whole time the prosthetic arm was operated, on-line training for the neural network had been performed. Then the subject was informed the discrimination result first half an hour, but was not informed it latter half an hour.

The time histories of limb function discrimination rates are shown in Fig.5. The solid line denotes the proposed method and the dashed line denotes the discriminant function method which does not have learning ability[7]. Both have maintained high success rates during the results are presented to the subject. But after stopping presenting the results, the discriminant function method indicates a marked decline in the success rate.

Fig.6(a) and (b) show the distributions of S_{ij} ($i=1,..,4$; $j=1$) of 10 times at pre-training and after an hour from the beginning of prosthetic arm control respectively. It is known that there are marked differences between both in terms of wrist supination, hand grasping and hand opening. Since

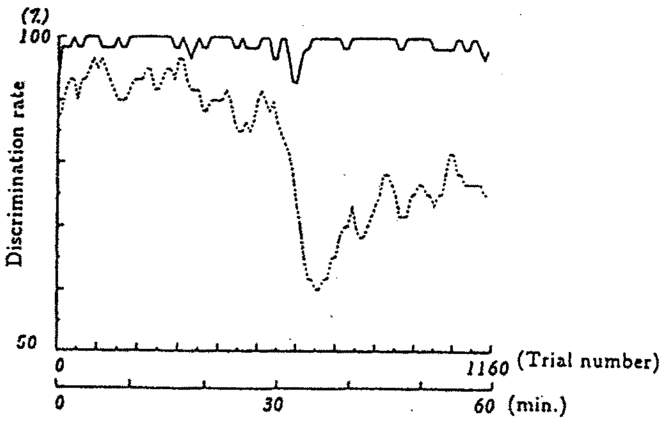

Fig.5 Time history of limb-function discrimination rates

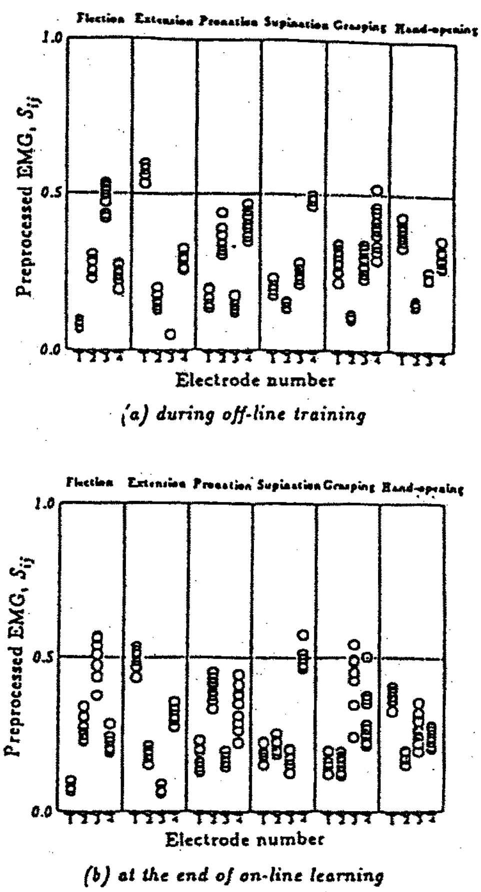

Fig.6 EMG pattern distributions

the proposed method is possible to be adapted to the variations of the subject's EMG pattens through learning, high success rates are maintained. This is very important in daily use of the prosthetic arm.

Photo.1 shows a example of hand grasping and opening by the amputee.

VI. CONCLUSION

This paper proposed the limb-function discrimination method using multichannel EMG signals by neural networks. Training of the neural network was able to be finished within several tens of iterations. Then the network after learning could identify distinct types of EMG signals that were generated by six separate arm functions. The success rate was more than 90% independently of the subjects and the electrode locations. Further re-training the neural network in use of the prosthetic arm made possible to correspond to the gradual changes of the EMG patterns resulting from muscle fatigue, sweating etc.

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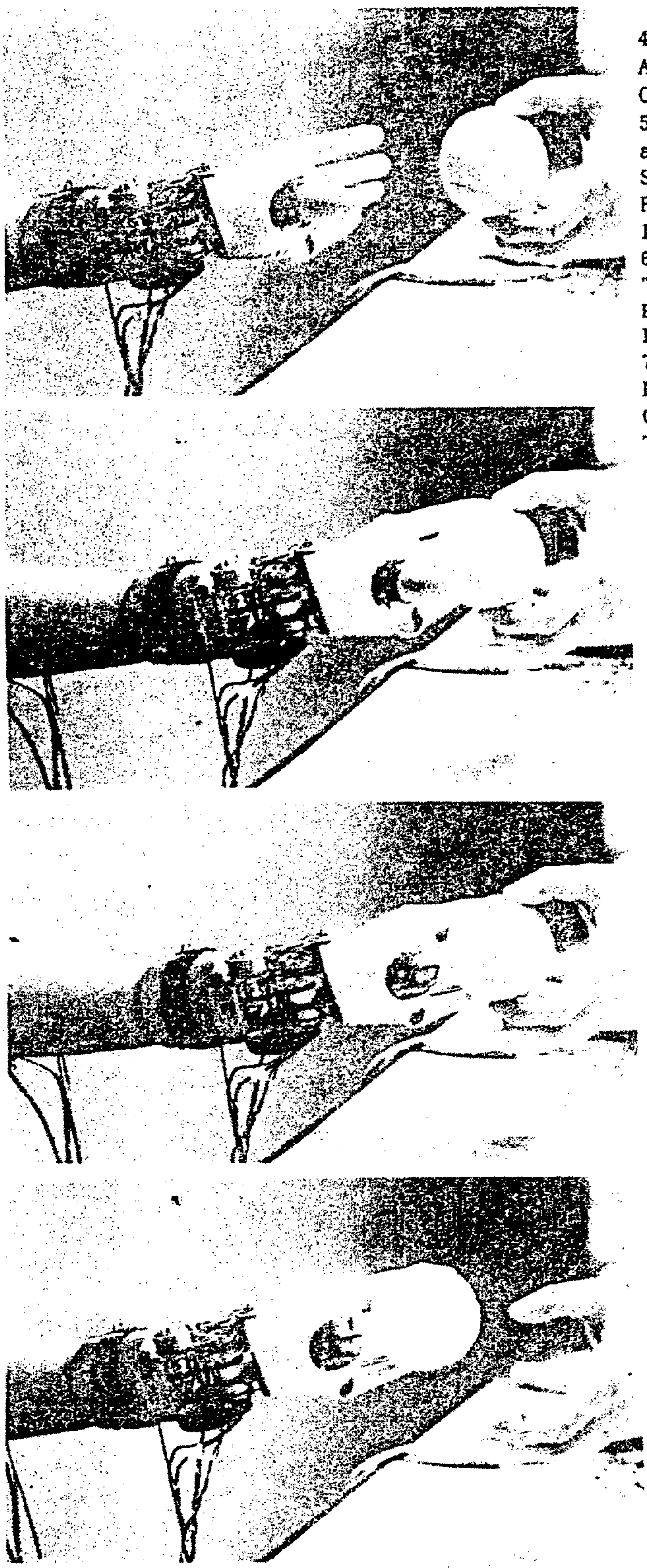

Photo.1 Hand opening and grasping.

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