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Limb-Function Discrimination using EMG Signals by Neural Network and Application to Prosthetic Forearm Control

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<Abstract> The present paper proposes a method to estimate the motion intended by an amputee from his EMG signals using the back propagation typed neural network. Estimation of the motion is one of the most important abilities to be provided by the amputee-prosthesis interface for the multifunctional powered prosthesis. The method presented here can discriminate the amputee's intended motion among six kinds of limb-functions from the multichannel 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 %, and can be adapted to some dynamic variations of the EMG signals by the back propagation learning.

1. INTRODUCTION

Even if we have lost limbs by traffic accidents etc. , the motion control area of the Central Nervous System(CNS) is still remained. Therefore, if a part of the muscles which have actuated the original limb are still remained after amputation and the surface EMG signal can be taken from them, the information of the intended motion must be reflected in the EMG. Consequently, it is expected that a natural feeling of control similar to that of the original limb can be realized using the EMG signals.

Several methods have already been reported on the motion discrimination using the EMG signal [1)-5)]. Almost of them relate the observed EMG data to stochastic sequences by linear difference equations(e.g. AR model). 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 largely 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 changes of electrode characteristics.

This paper describes a discrimination method by neural networks which can be adaptable to the gradual changes of the EMG patterns. An early work has been done to explore the application of neural networks to EMG analysis [6)]. Then, the neural networks composed of two separate subsystems were proposed. First, a Hopfield network is used to extract features from an EMG signal. Second, an error-back propagation neural network is used to classify the feature set. EMG data were collected from a male subject who had acquired amputation leaving a very short below elbow stump. Discrimination among elbow extension, elbow flection, wrist pronation and wrist supination was found without any subject training prior to data collection. It was shown that with an appropriate selection of the gain parameter in the learning algorithm it was possible to achieve successful network classification of all the training data sets within 2768 iterations. In their method, however, iterations for learning are too many for the purposes of controlling prosthetic arms. Further, there are no mention of the network classification for the EMG patterns other than the training data sets.

In this paper, we proposed a method which can discriminate the amputee's intended motion among six kinds of limb-functions using the multichannel 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. It is shown that after several tens of training iterations, 90 percent correct classification level can be achieved. Then the method proposed is applied to control of a prosthetic forearm with three degrees of freedom.

2. LIMB-FUNCTION DISCRIMINATION BY NEURAL NETWORK

Fig.1 shows a flow chart of the limb-function discrimination procedure proposed here, which is

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composed of band-pass filters, rectification, smoothing filters and neural network.

2.1 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.

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

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 jth band-pass filter (j=1,2,...,N) and $y_{ij}(t)$ is the output of the jth band-pass filter with the EMG $x_i(t)$.

2.2 Rectification and smoothing

The $N\times L$ EMG signals obtained from the band-pass filters are rectified and passed through individual one-pole Butterworth filters each with a low pass cut off 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

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

Further, Z_{ij} is normalized by

$$S_{ij} = \frac{Z_{ij}}{\sum_{i=1}^{L} Z_{ij}} \quad (3)$$

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

2.3 Neural network subsystem

A feedforward type neural network is used to classify the rectified and smoothed EMG signals [7]. The neural network consists of an input layer of $L\times N$ 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 u_i and output o_i of the unit i are defined as follows.

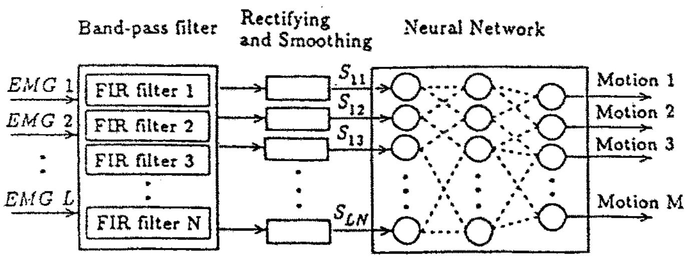


Fig.1 A limb-function discrimination method using the neural network

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

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

(hidden and output layer units)

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,

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

2.4 Network pretraining

After attaching the prosthetic forearm, the amputee is asked to perform each of M kinds of motions. Then M EMG data are divided into $M\times n$ data sets as stated in 3.1. The neural network is trained by error back propagation algorithm. using these $M\times n$ 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 other units became less than 0.2 for each motion. Further the initial values of the network weights are uniform random numbers such that $|W_{ij}|<1.0$.

2.5 Function discrimination

It is assumed that the amputee intends to make one of M motions. Then the EMG signals are observed 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 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.

Table 1 Results of limb-function discrimination experiments

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 (%)	3.6	5.7	8.7	12.0	13.4

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

2.6 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 set of teacher's signals. Then delete the oldest one of the stored teacher's signals ($M \times n$ patterns).

2) Train the network weights using the updated set of 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.

Note that this procedure is equivalent to apply Hebb's unsupervised learning rule to the multi-layer neural network [8].

3. PROSTHETIC FOREARM CONTROL

3.1 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

There are six motions ; wrist flection, wrist extension, forearm pronation, forearm supination, hand grasping, and hand 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 measurement

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 1. 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.

Separately from training data, each of M kinds of motions were performed by 100 times and the EMG signals were used to confirm the function discrimination after learning.

Table 1 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.

Fig.2 shows an example of learning process of the experiment No.1. The abscissa is the number of iterations and the ordinate is mean squared error E as follows.

$$E = \sum_{j=1}^{60} \sum_{i=1}^{6} \frac{(o_i^{(j)} - t_i^{(j)})^2}{60} \tag{7}$$

where $o_i^{(j)}$ is the unit output of the output layer and $t_i^{(j)}$ is the desired output. The error decreases monotonously during training.

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.3.* 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.

3.2 Prosthetic forearm control experiments

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. Photo 1 shows the experimental situations. 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.

Fig. 4 shows time histories of limb function discrimination rates. The solid line denotes the proposed method and the dashed line denotes the discriminant function method which does not have learning ability [9]. 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.5 (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 the proposed method is possible to be adapted to the variations of the subject's EMG patterns through learning, high success rates are maintained. This is very important in daily use of the prosthetic arm.

Now *Fig.6* shows the number of iterations at each of on-line training in Fig.4. It is known that

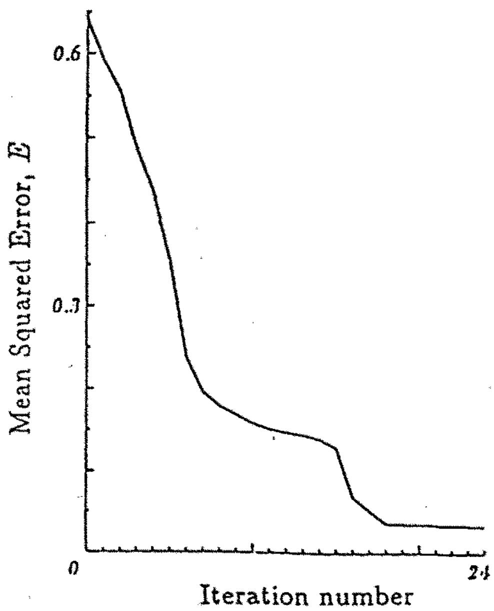


Fig.2 An example of convergence behavior during network pretraining

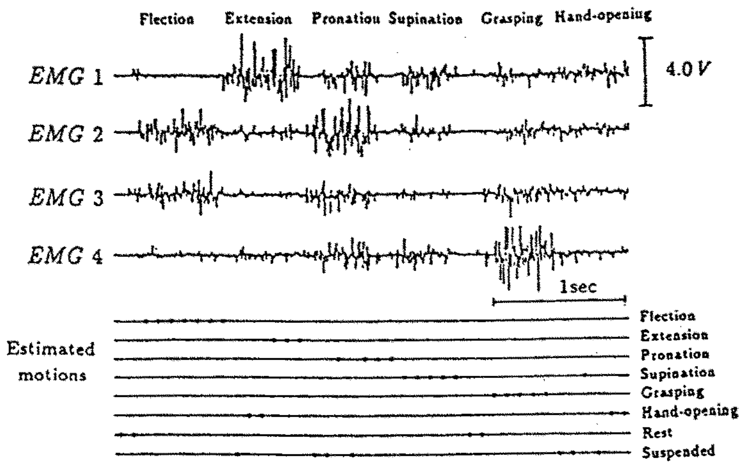


Fig.3 Discrimination results of a series of motion (amputee)

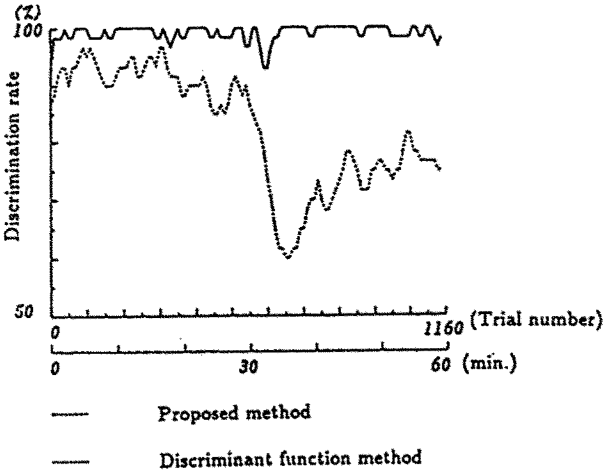
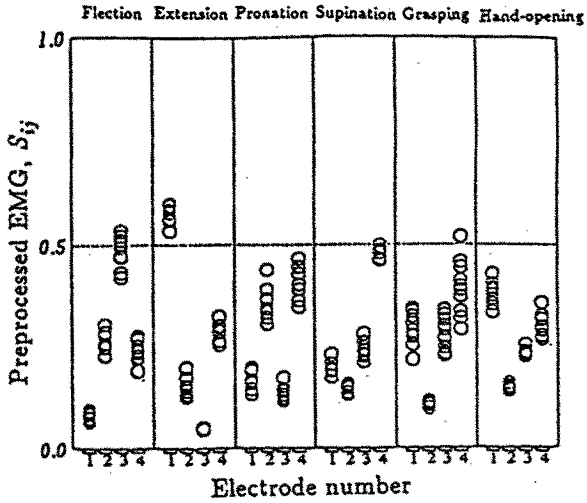
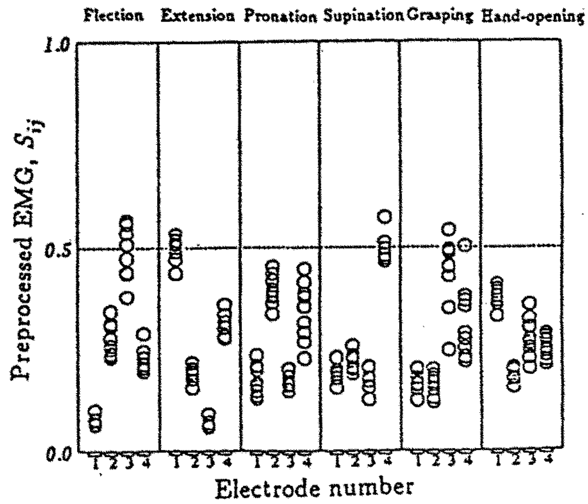


Fig.4 Time history of limb-function discrimination rates



(a) during off-line training



(b) at the end of on-line learning

Fig.5 EMG pattern distributions

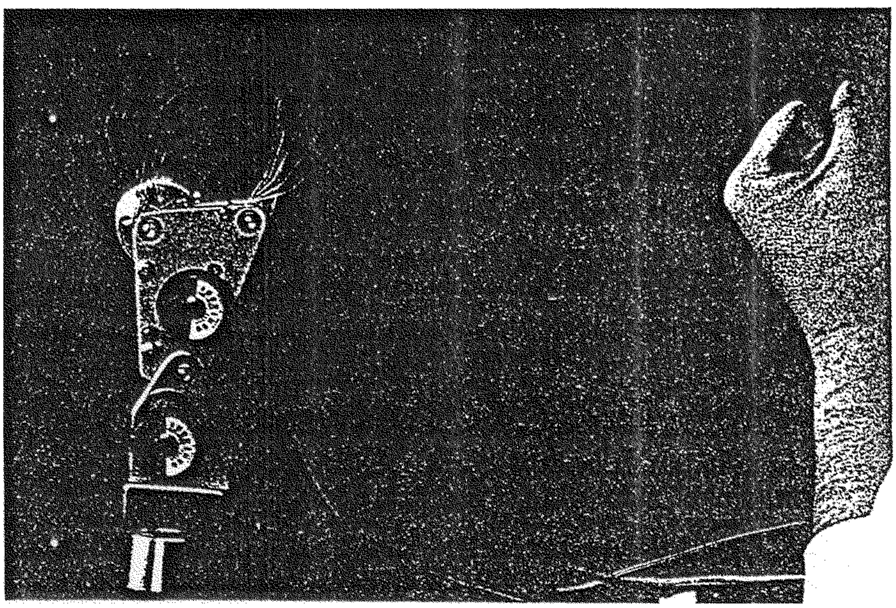


Photo.1 Control of the prosthetic forearm