Systems and Computers in Japan, Vol. 18, No. 12, 1987
Translated from Denshi Tsushin Gakkai Ronbunshi, Vol. 70-D, No. 1, January 1987, pp. 207-215

A Limb-Function Discrimination Method Using EMG Signals for the Control of Multifunctional Powered Prostheses

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SUMMARY

This paper describes a method to estimate the motion intended by an amputee from his EMG symbols. This is one of the important abilities to be provided by the amputee-prosthesis interface within the multifunctional powered prosthesis. To make the interface easy for the amputee to use, the measurement of EMG should be simplified as much as possible. Up to now, the function discrimination by the surface EMG has been employed, where a particular muscle must be specified for the EMG electrode. This imposes a restriction in the electrode placement, and restricts the function discrimination ability. From such a viewpoint, this study aims at the development of the discrimination method, where the electrode locations are made flexible by utilizing the cross-information among the electrodes as well as the amplitude and frequency characteristics of the EMG. The method proposed is a combination of the multidimensional AR model and the discriminant function. It is shown by the experiment for 3 subjects and 4 electrode locations that the proposed method can discriminate, with the accuracy above 93 percent, 6 motions of forearm and hand, using 4 pairs of electrodes and EMG for 100 ms after motion generation. Thus, the discrimination proposed in this paper can simplify the electrode placement, and realize a high discriminating ability.

1. Introduction

One of the most important problems in the powered limb prosthesis is the acquisition of the control signal. From an idealistic viewpoint, the prosthesis control matched to the central nervous motion-control system of an amputee can be realized if the control signal is obtained directly from the afferent nerves of the amputee.

As far as such an ideal method is difficult to realize, the electromyograph (EMG) is one of the most promising control signal sources. It is a trace of the electrical activity of the neuromuscular system. Consequently, one can expect that a natural feeling of control close to that of the original limb can be realized by using EMG from the muscle, which is left in the amputee. Especially, the surface EMG has a feature that it is easy to measure without any danger.

On the other hand, EMG is a complex of a large number of action potentials of muscle fibers. It contains considerably higher frequency components [1]. Consequently, to utilize EMG as the control signal for the limb-prosthesis, there must be a certain amputee-prosthesis interface. Figure 1 is an example of the amputee-prosthesis interface in the multifunctional powered prosthesis.

EMG is observed from the muscle left in the amputee, and the motion intended by the amputee, such as flexion, extension, pronation and spination, is estimated. In parallel to the estimation, the signal to drive and control the prosthesis (corresponding to the muscle force) is produced from EMG. The estimated motion is realized by the proportional control by the manipulation signal [2, 3]. On the other hand, the signal corresponding to the position, velocity or sensation of force are fed back to the amputee in the form of a tactile sensation, a visual sensation or an electrical stimulation.

This paper discusses the motion estimation. EMG information which can be used in the estimation are the amplitude and the frequency. The amplitude pattern of EMG exhibits features corresponding to various motions, since different muscles work with different degrees of contraction, depending

ISSN0882-1666/87/0012-0042$7.50/0

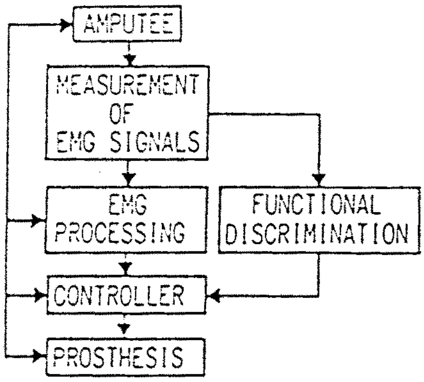


Fig. 1. Amputee-prosthesis interface.

on the kind of motion. On the other hand, the frequency pattern also exhibits features corresponding to various motions, since the muscles have different frequency characteristics [4, 5] and the transfer function of the tissue depends on the distance between the muscle and the electrode [1]. Several studies have already been reported on the estimation of the motion utilizing those EMG [6 - 10].

Graupe et al. modelled EMG measured by a pair of electrodes by an AR model, and presented a function discrimination method utilizing the parameters depending on the kind of motion [6]. Their method is based largely on the frequency characteristics of EMG. Yamada et al. proposed the function discrimination by the discriminant functions, where the rectified integration of EMG from several electrodes is used as the feature vector [8]. This method utilizes both the amplitude and the frequency data by employing a bandpass filter.

However, those methods specify a particular muscle to place the electrodes, and the electrode locations must be determined carefully. In the actual use of the prosthesis, inevitably there are produced a deviation of the electrode location or the difference of the muscle characteristics due to the different amputation. Consequently, there must be a means to minimize those effects.

From such a viewpoint, this paper aims at the function discrimination, where the electrode locations are made relatively flexible by utilizing the cross-information among the electrodes as well as the amplitude and frequency characteristics. The proposed method is a combination of the multidimensional AR model and the discriminant function. The frequency characteristics, including the cross information of EMG are utilized by the multidimensional AR model, and the amplitude patterns of EMG are utilized by the discriminant function.

In the following, Sect. 2 describes the discriminating algorithm. Section 3 discusses from experimental viewpoint the effects of EMG observation time and the order of the AR model on the discriminating ability. Section 4 describes the simulation experiment for the prosthesis to evaluate the effect of the electrode placement and the difference of subjects.

2. Function Discrimination by Multichannel EMG

2.1 Multidimensional AR model

It is noted that the frequency characteristics of EMG exhibit different features depending on motions, and EMG from several electrodes are modelled by the multidimensional AR model [11]. It is assumed that EMG is a stationary random signal with mean 0. Let EMG signal $X_m(t)$, generated with motion m ($m = 1, 2, \cdots, M$, where M is the number of different motions which are considered), be

$$X_m(t) = -\sum_{k=1}^{p} A_m(k) X_m(t-k) + e_m(t) \tag{1}$$

Letting the number of electrode pairs be L, $X_m(t)$ is an L-dimensional column vector; p is the order of AR model; $A_m(k)$ is the $(L \times L)$ AR coefficient matrix of kth order; $e_m(t)$ is the prediction error vector. It is assumed that $e_m(t)$ is an L-dimensional white Gaussian vector satisfying

$$E[e_m(t)] = 0 \tag{2}$$

$$E[e_m(t) \cdot e_m^T(s)] = V_m \delta_{ts} \tag{3}$$

where

$$e_m(t) = [e_{m1}(t)\ e_{m2}(t) \cdots e_{mL}(t)]^T$$

$$V_m = \begin{bmatrix} E[e_{m1}(t)e_{m1}(t)] \cdots E[e_{m1}(t)e_{mL}(t)] \\ \vdots \qquad \ddots \qquad \vdots \\ E[e_{mL}(t)e_{m1}(t)] \cdots E[e_{mL}(t)e_{mL}(t)] \end{bmatrix}$$

$$\delta_{ts} = \begin{cases} 1 & (t = s) \\ 0 & (t \neq s) \end{cases}$$

The superscript T denotes the transpose.

All the information contained in the EMG signal $X_m(t)$ is represented by the AR coefficient matrix $A_m(k)$ and the covariance matrix V_m of the prediction error. Especially, the nondiagonal elements of $A_m(k)$ and

V_m represent the cross information among the electrodes.

The AR coefficient matrix $A_m(k)$ is estimated so that the mean square of the prediction error,

$$E_m = E[e_m^T(t)e_m(t)] = \text{trace}\, V_m \tag{4}$$

is minimized. Thus, E_m represents the extent of fit to the AR model to EMG.

2.2 Discriminant function

The variance of the prediction error $e_m(t)$ of the AR model reflects the amplitude characteristics of EMG signals. Since EMG exhibits different features. From such a viewpoint, the discriminant function is constructed using the variance $E[e_{mi}^2(t)]$ of the prediction error for each electrode pair as the characteristic values.

The following normalization is made to eliminate the effect of the muscle force on the pattern variation:

$$S_i^{(m)} = E[e_{mi}^2(t)]/E_m \quad (i = 1, 2, \cdots, L) \tag{5}$$

$$\sum_{i=1}^{L} S_i^{(m)} = 1.0$$

In general, if the number of motions to be discriminated is M, there must be constructed $M(M - 1)/2$ discriminant functions. When M is increased, however, a long computation time is a problem. From such a viewpoint, a method is employed in the following, which can discriminate M motions using a fewer number of discriminant functions [12].

Assume that $n_1, n_2, \cdots, n_M$ data were obtained for different motions. Let the nth characteristic value of the motion m be $S_{ni}^{(m)}$ ($n = 1, 2, \cdots, n_m$; $i = 1, 2, \cdots, L$). Then the within-group square-sum, product-sum matrix $W = (W_{ij})$, representing the variance in a motion, and the between-group square-sum, product-sum matrix $B = (B_{ij})$, representing the variance among motions, are given by

$$W_{ij} = \sum_{m=1}^{M} \sum_{n=1}^{n_m} (S_{ni}^{(m)} - \bar{S}_i^{(m)})(S_{nj}^{(m)} - \bar{S}_j^{(m)}) \tag{6}$$

$$B_{ij} = \sum_{m=1}^{M} n_m (\bar{S}_i^{(m)} - \bar{S}_i)(\bar{S}_j^{(m)} - \bar{S}_j) \tag{7}$$

where

$$\bar{S}_i = \sum_{m=1}^{M} n_m \bar{S}_i^{(m)}/N : \text{total mean}$$

$$N = \sum_{m=1}^{M} n_m \qquad : \text{total number of trials}$$

The aim is to determine K discriminant functions Z_l ($l = 1, 2, \cdots, K$):

$$Z_l = \sum_{i=1}^{L} a_{li}(S_i - \bar{S}_i) \quad (l = 1, 2, \cdots, K) \tag{8}$$

To simplify the discrimination procedure, the within group square sum of Z_l should be small and the between-group square sum should be large. From such a viewpoint, the coefficient a_{li} is determined by the condition that the ratio of the between-group square-sum to the within-group square sum is maximized. Let the within-group square-sum of Z_l be S_{Wl}, and the between-group square-sum be S_{Bl}:

$$S_{Wl} = \sum_{m=1}^{M} \sum_{n=1}^{n_m} (Z_{nl}^{(m)} - \bar{Z}_l^{(m)})^2$$
$$= \sum_{i=1}^{L} \sum_{j=1}^{L} a_{li} a_{lj} W_{ij} \tag{9}$$

$$S_{Bl} = \sum_{m=1}^{M} n_m (\bar{Z}_l^{(m)} - \bar{Z}_l)^2$$
$$= \sum_{i=1}^{L} \sum_{j=1}^{L} a_{li} a_{lj} B_{ij} \tag{10}$$

Differentiating $\theta = S_{Bl}/S_{Wl}$ by a_{li}, and equating the result to 0,

$$(B - \theta W)a_l = 0 \tag{11}$$

For this equation to have a solution other than $a_i = 0$, there must hold

$$|B - \theta W| = 0 \tag{12}$$

or

$$|W^{-1}B - \theta I| = 0 \tag{13}$$

Consequently, θ is an eigenvalue of the matrix $W^{-1}B$.

Both W and B are $L \times L$ matrices; W is nonsingular, and the rank of B does not exceed the degree of freedom ($M - 1$) among the groups. Consequently, the rank of $W^{-1}B$ does

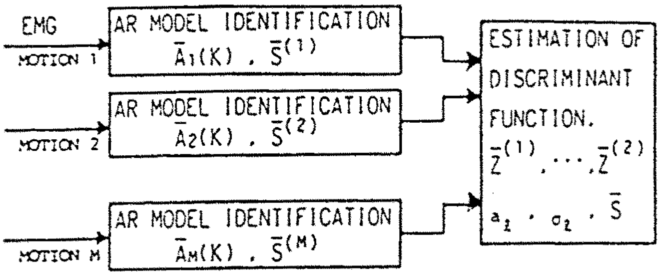


Fig. 2. Procedure of model identification.

not exceed min{L, M - 1}. The coefficient vectors a_l of the discriminant function are the right eigenvectors arranged in the descending order of the eigenvalues. If the eigenvalues satisfy $\theta_i = \theta_j$, the corresponding right eigenvectors a_i and a_j are orthogonal, indicating that Z_i and Z_j are uncorrelated in the group [12].

2.3 Discrimination algorithm

The discrimination algorithm is composed of the model identification and the function discrimination. The model identification determines the parameters for each motion needed in the discrimination. The function discrimination assumes that a particular motion among the set of considered motions is intended by the controller. EMG for that motion is compared with the model of each motion, and the one with the best fit is adopted.

(1) Model identification

The controller is asked to perform M considered motions by n_M times for each. EMG signals are recorded. Then using the multidimensional Ar model [Eq. (1)], AR coefficient matrix $A_m(k)$ (m = 1, 2, $\cdots$, M; k = 1, 2, $\cdots$, p) and the covariance matrix V_m(m = 1, 2, $\cdots$, M) of the prediction error are estimated. The discriminant functions are determined using the variance $S_i^{(m)}$ [Eq. (5)] of the prediction error for each electrode pair:

$$Z_{jl}^{(m)} = \sum_{i=1}^{L} a_{li}(S_{ij}^{(m)} - \bar{S}_i) \tag{14}$$
$$(j=1,\ 2,\ \cdots,\ n_m,\ l=1,\ 2,\ \cdots,\ K)$$

For each motion, the mean $\bar{Z}_l^{(m)}$ and the within-group variance σ_l of $Z_{jl}^{(m)}$

$$\bar{Z}_l^{(m)} = \frac{1}{n_m}\sum_{j=1}^{n_m} Z_{jl}^{(m)} \tag{15}$$

$$\sigma_l = \frac{1}{n_m M - 1}\sum_{m=1}^{M}\sum_{j=1}^{n_m}(Z_{jl}^{(m)} - \bar{Z}_l^{(m)})^2 \tag{16}$$
$$(l=1,\ 2,\ \cdots,\ K)$$

are calculated. The mean AR coefficient matrix $\bar{A}_m(k)$, the total mean $\bar{S}_i$ (i = 1, 2, $\cdots$, L) of the characteristic value, the transformation vector a_l, the mean of the discriminant function $\bar{Z}_l^{(m)}$, and the within-group variance of the discriminant function σ_l are stored in the computer (Fig. 2). They are used in the function discrimination.

(2) Function discrimination

It is assumed that the amputee intends to make one of M motions. The EMG signal $X(t)$ is observed and compared with the AR model for each motion, which is determined by the model identification procedure. The prediction $\hat{X}_m(t)$ for $X(t)$ is given as follows using the matrix $\bar{A}_m(k)$:

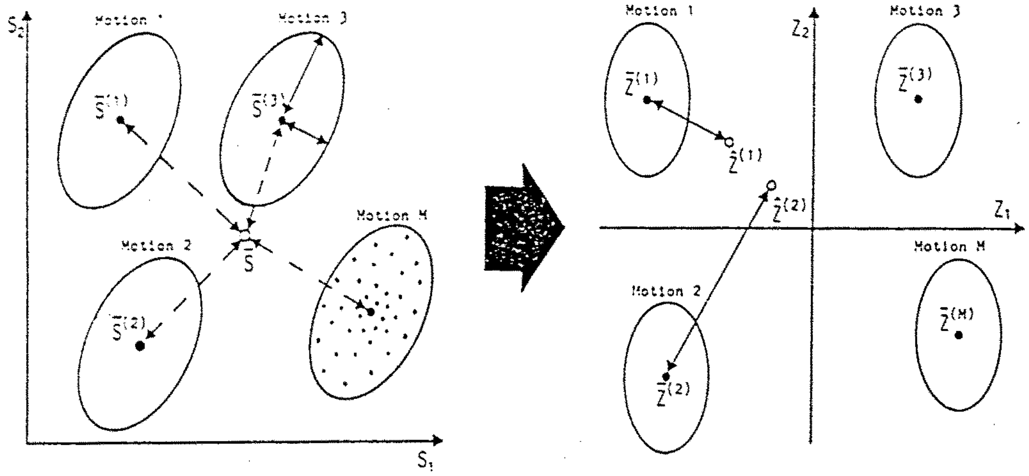
$$\hat{X}_m(t) = -\sum_{k=1}^{p}\bar{A}_m(k)X(t-k)$$
$$(m=1,\ 2,\ \cdots,\ M) \tag{17}$$

The prediction error $\hat{e}_m(t)$ is given by

$$\begin{aligned}\hat{e}_m(t) &= X(t) - \hat{X}_m(t)\\ \hat{e}_m(t) &= [\hat{e}_{m1}(t)\hat{e}_{m2}(t)\cdots\hat{e}_{mL}(t)]^T\end{aligned} \tag{18}$$

Letting the number of data be N, the square-sum of the prediction error $\hat{E}_m$ is given by

$$\hat{E}_m = \sum_{i=1}^{L}\sum_{t=p+1}^{N}\hat{e}_{mi}^2(t) \tag{19}$$



(a) characteristic values (b) discriminant function

Fig. 3. Schematic representation of discriminant function method.

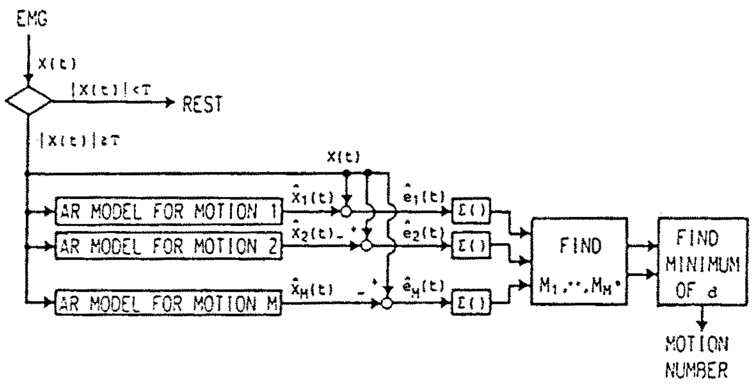


Fig. 4. Procedure of limb-function discrimination.

Since the AR coefficient matrix for each motion is determined to minimize the mean square of the prediction error, one can conclude that the fit to the model is better if $\hat{E}_m$ is smaller. From such a viewpoint, the square sum of the prediction error $\hat{E}_m$ is calculated for each motion model using the observed EMG $X(\tau)$, and the motion to consider is limited to M^* with smaller $\hat{E}_m$. Then the discriminant function is calculated.

Since the frequency characteristics of EMG do not depend on the muscle force level [13, 14], the processing up to this point does not depend on the amplitude of EMG (i.e., the force of the controller). The processings can be performed in parallel for different motions, thereby reducing the computation time.

Using the characteristic values of $\hat{S}_i^{(m)}$ ($m = 1, \cdots, L$; $m = M_1, M_2, \cdots, M_{M^*}$) of M^* motions with smaller $\hat{E}_m$, the discriminant functions

$\hat{Z}_l^{(m)}$,

$$\hat{Z}_l^{(m)} = \sum_{i=1}^{L} a_{li}(\hat{S}_i^{(m)} - \bar{S}_i) \quad (l = 1, 2, \cdots, k) \tag{20}$$

are calculated. The motion with the minimum Mahalanobis generalized distance d from the mean pattern $\bar{Z}_l^{(m)}$ of each motion is selected. Mahalanobis distance generalized distance is the distance defined considering the channel variance of the discriminant function. It is defined as follows:

$$d^{(m)} = \sum_{l=1}^{K} [(\hat{Z}_l^{(m)} - \bar{Z}_l^{(m)})^2]/\sigma_l^2 \tag{21}$$

Figure 3 is an illustration of the discriminant function for electrode pairs L being 2. Figure 3(a) is the characteristic values obtained from the prediction error of the AR model. After n_m trials for each motion, a cluster is formed on the plane of the characteristic value for each motion. The within-group variance [Eq. (6)] indicates the variance within each motion, and the between-group variance [Eq. (7)] indicates the variance among different motions. To simplify the discrimination between groups, the ratio of the between-group variance to the within-group variance is maximized.

Using thus determined orthogonal transformation vector a_l, the characteristic value is converted into the discriminant function (b); $\bar{Z}^{(m)}$ is the mean of each motion; $\hat{Z}^{(1)}$ and $\hat{Z}^{(2)}$ indicate the discriminant values which fit well to the AR model. In this case, the mean $\bar{Z}^{(1)}$ of motion 1 has less distance, and motion 1 is decided as the motion intended by the controller. It should be noted that the within-group variance of the discriminant function for each motion is assumed as constant, independent of the motion. This point will be discussed in the next section.

Figure 4 is the block diagram of the motion discrimination. It is assumed that the motion is intended when the EMG amplitude exceeds a certain threshold T. Then the function discrimination is started. It is possible to regard the rest state as a motion and it may be included in the motions to be considered.

3. Function Discrimination Ability and Effect of Parameters

This section discusses the discrimination ability of the function discrimination by multichannel EMG described up to the previous section. A basic experiment was performed. The proposed method includes several parameters. Among those, the number of data in the function discrimination, the order of AR model, and the number of trials in the model identification are considered in the following. Those parameters must be set so that the discrimination rate is high and less time is required for discrimination. In general, the accuracy of the estimation is improved by increasing the number of data, the order of the model and the number of trials. In this case, the discrimination rate is improved, while the time for discrimination is increased. Thus, there must be a compromise in the choice of those parameters. From such a viewpoint, the relation between the discriminating ability and the parmeters is examined experimentally. Then the parameters are set from a practical viewpoint.

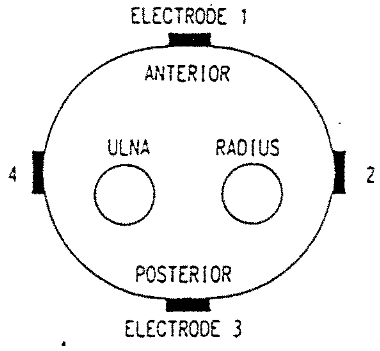


Fig. 5. Electrode locations.

3.1 Experimental conditions

The conditions of the experiment were as follows.

(1) Motions

There are six motions: palmerflexion, dorsiflexion, pronation, supination, grasp and open.

(2) Sites of measurement

Four pairs of electrodes were attached with 90-deg difference on the forearm, 7 cm from the elbow joint (Fig. 5). The electrode is a concentric disposable type with the diameter of 1.5 cm (Nihon Kohden Co.). Bipolar lead with electrode spacing of 2 cm was employed. EMG in each channel is sent from the medical telemeter (Nihon Kohden Co.), amplified and passed through the low-pass filter (first-order analog filter with cut-off at 1 kHz). The signal is A/D converted with the sampling frequency of 2 kHz. The result is stored in the digital computer as the data file.

(3) Subject

One adult male (normal).

(4) Parameter in model identification

2000 data were prepared for each channel. The order P of the AR model was set as 2, 4, 6 or 8. The number of trials for each motion n_m was set as 5, 10 or 15 (m = 1, 2, $\cdots$, 6). The data were observed for 1 s (2000 × 0.5 ms). The number of data in the model identification was set as a relatively large value based on the following

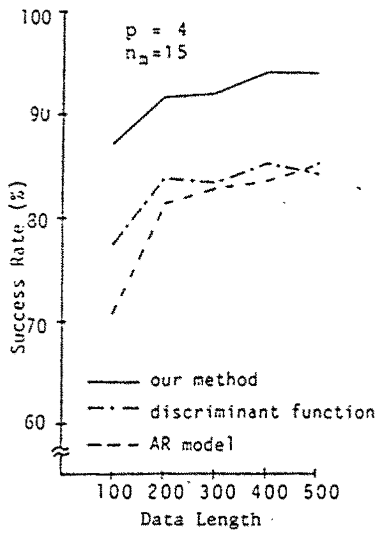


Fig. 6. The effect of data length on success rate.

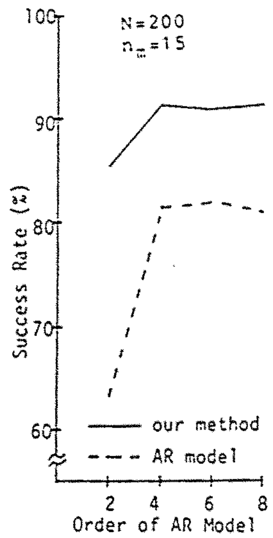


Fig. 7. The effect of model order on success rate.

observation. In the preliminary experiment, if the number of data is decreased, the estimation accuracy of the model is degraded, affecting the function discrimination.

(5) Function discrimination parameter

The number N of data per channel was set as 100, 200, 300, 400 or 500 (the observation time being 50, 100, 150, 200 or 250 ms, respectively). For each motion, EMG was observed fifty times. Using the square sum E_m of the prediction error, the number of the motion to consider $M*$ was limited to 2, and the discriminant function was calculated.

Under those experimental conditions, EMG was observed, and the function discrimination was performed. LWR algorithm [11] was used in the estimation of the AR model, and the Everline method [14] was used in the solution of the eigenvalue problem of Eq. (13).

3.2 Experimental result and analysis

Figure 6 shows the relation between the number of data in the function discrimination and the discrimination ability. The abscissa is the number of data and the ordinate is the discrimination rate, which is the ratio of the correct discrimination in 300 trials. In the future, the solid line is the discrimination rate of the proposed method, and the dashed line is the case where the function discrimination is made using only the AR model. The dot-dash line shows the case where the discrimination is made using only the discriminant function with the square-sum for each EMG channel as

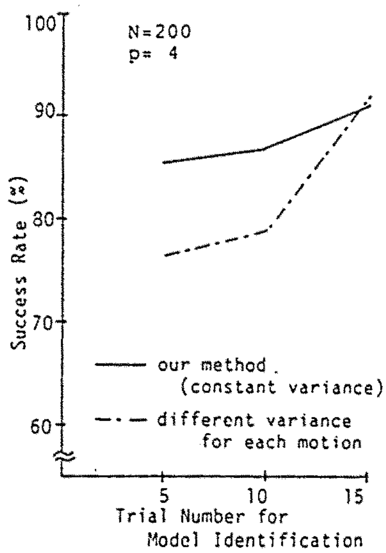


Fig. 8. The effect of trial numbers for model identification on success rate.

the characteristic value. The number of trials in the model identification was 15 for each motion, and the order of AR model was set as 4.

It is seen that the discrimination rate is improved by 10 to 15 percent, compared with the case where the AR model or the discriminant function is used independently. It should be noted that AR model and the discriminant function utilizes the frequency and amplitude information of EMG, respectively, while the proposed method utilizes both the frequency and amplitude information. From the viewpoint of reducing the time for observing EMG, the number of data should be minimized. It is seen from the figure that although the discrimination rate is improved by increasing the number of data, the improvement is not very remarkable for the number of data exceeding 200. This corresponds to the observation time of 100 ms.

When the number of data is set as 100, the discrimination rate is degraded drastically. This can be due to the following two reasons. One is the degradation of the estimation accuracy of the prediction square-sum E_m of error with the decrease of the data. The other is the nonstationarity of EMG immediately after the onset of the motion. When the data are decreased, EMG immediately after the onset of the motion must be utilized, violating the stationarity assumption in AR model. The data cannot consequently be reduced further.

Figure 7 shows the discrimination rate for AR model of orders 2, 4, 6 and 8. The solid line is the discrimination rate of the proposed method, and the dashed line is the case where only the AR model is employed. The number of data is 200, and the number of trials is 25 for each motion in the model identification. It is seen from the figure that the discrimination rate is improved with the increase of the order. When the order exceeds 4, however, the discrimination rate is not increased remarkably. Consequently, the order of 4 will be sufficient.

In general, AIC is used in the determination of the order of the AR model. By applying this idea, the order is determined as 20 or more for EMG. On the other hand, it is reported that the multiple correlation coefficient between EMG and the value predicted by AR model saturates beyond the 4th order [7]. AIC for the multidimensional AR model is given by [11]

$$\mathrm{AIC}(p)=\ln[\det V(p)]+2pL^2/N \qquad (22)$$

where p is the order of AR model, V is the covariance matrix of prediction error; N is the number of data in the model identification, and L is the number of channels (number of electrode pairs). In this case, N = 2000 and L = 4. Consequently, the second term in the right-hand side is considerably small, having little effect on AIC. As in this method, where the prediction error is employed mostly rather than the AR coefficient, the multiple correlation coefficient corresponding to the first term on the right-hand side can be used as the criterion for determining the order.

Figure 8 shows the relation between the number of trials in the model identification and the discrimination rate. The number of data in the motion discrimination is set as 200, and the order of the AR model is set as 4. The solid line is the discrimination rate of the proposed method. The discrimination rate tends to be degraded with the decrease of the number of trials. This is due to the degradation of the estimation accuracy for each motion model.

In the proposed method, it is assumed that the within-group variances of the discriminant function are constant, independently of the motion (2.3). As a result of experiment, however, the within-group variances depend little on the kind of motion. From such a viewpoint, the method based on Mahalabinos distance of the discriminant function with different within-group variances is also examined. The dashed line in the figure indicates the discrimination rate for that method.

When the model is estimated by 15 trials for each motion, the discrimination rate is slightly better if the difference of the variance is taken into consideration. When the number of trials in the model identification is decreased, the discrimination rate in the new method is degraded drastically. This is due to the degradation of the estimation accuracy for the variance with the decrease of the number of trials. Consider the case where the number of trials is 5. Then in the method assuming the constant variance, the variance is estimated from 6 motion × 5 trials = 30 data. If the different variances are assumed, one must estimate the variance from 5 data for each motion.

The number of trials in the model identification does not affect the time required in the motion discrimination, but should be reduced as much as possible from a practical viewpoint. From such a viewpoint, it is desirable to assume that the within-group variances are constant to realize a higher discrimination rate. As a result of experiment, it is indicated that the discrimination rate of approximately 86 percent can be realized by the method proposed in this paper, for 5 trials for each motion in the model identification, 4th-order AR model and 200 data per channel in the motion discrimination. The next section describes the experiment for the actual prosthesis control to verify the effectiveness of the method.

4. Motion Discrimination Experiment

When the prosthetic hand is used, the controller can determine the result of control in real-time by observing the motion

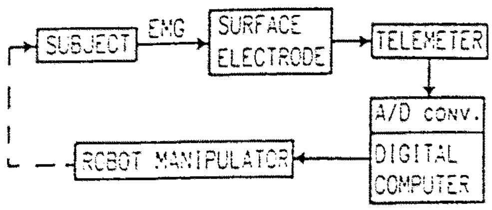


Fig. 9. A block diagram of experimental arrangements.

of the prosthesis. From such a viewpoint, the experiment was made by feeding back the discrimination result to the subject. By this scheme, the subject can utilize his own learning and adaptive ability in the experiment. The experiment was also made to examine the effect of the subject and electrode placements, to indicate the discriminating ability of the proposed method.

Figure 9 shows the structure of the experimental set-up. EMG signals from the surface electrodes are sent to the medical telemeter and are amplified. The data are stored in the digital computer through the A/D converter. The result of discrimination is sent to the manipulator (MOVE MASTER II, Mitsubishi Corp.), and the subject can determine the result of discrimination by the motion of the manipulator.

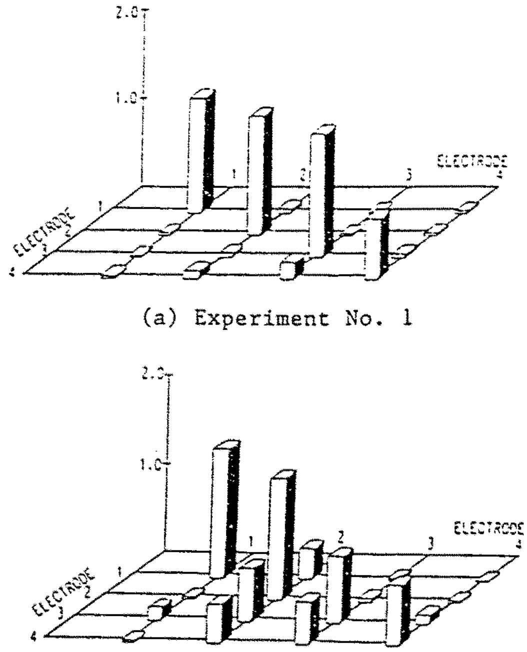
The conditions of the experiment were the same as in Sect. 3.1. Based on the result of the experiment in Sect. 3, the number of trials in the model identification was set as 5 for each motion. The order of the AR model was set as 4, and 200 data were used in the motion discrimination. Three adult males (normal) were employed as the subjects. Two electrode placements were tried for each subject, and the discrimination rates were determined.

Table 1 shows the electrode placements and the discrimination rate. The discrimination rate exceeding 93 percent was obtained for each electrode placement. Especially, the experiment with No. 1 is the result for the same electrode placement as in the previous section. Table 2 shows the discrimination for each motion. There is a tendency that incorrect discrimination is often produced by deciding the dorsiflexion for open and the palmer flexion for grasp. However, the discrimination rate of 96 percent was achieved in total. This is an improvement of approximately 10 percent compared with 86 percent in the previous section, which is the result of feedback.

Table 1 also shows the result of discrimination for the same EMG using only the AR model. It is seen that when the electrodes are close to each other (Nos. 2, 4 and 6), the discrimination is almost the same as in the case where the AR model and the discriminant function are combined. The reason seems to be that EMG from the electrodes close to each other have a high correlation, and the cross information among the electrode pairs are utilized fully in the discrimination.

Figure 10 shows the absolute value of the AR coefficient matrix. This is the value obtained in the identification for palmer flexion AR model of the first order, with (a) for No. 1 and (b) for No. 2. It is seen that the absolute values of the diagonal elements in the coefficient matrix are nearly the same, but those of the off-diagonal elements are several to more than ten times larger in No. 2. An exception is the cross-term between electrodes 1 and 4, which is decreased in No. 2 due to the larger distance between electrodes.

The asymmetry of Ar coefficient matrix in (b) of the figure should be noted. It is seen from the figure that (1, 2), (3, 2), (4, 2) and (4, 3) elements of the AR coefficient matrix have larger values, while (2, 1), (2, 3), (2, 4) and (3, 4) elements are relatively small. This indicates that the source of EMG (major working muscle) is close to electrode 2. Thus, the AR coefficient matrix contains the spatial information



(a) Experiment No. 1

(b) Experiment No. 2

Fig. 10. Coefficient matrices of AR model (absolute values).

Table 1. Function discrimination experiment

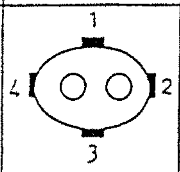
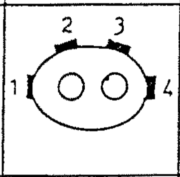
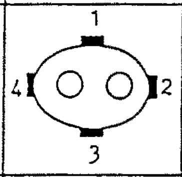
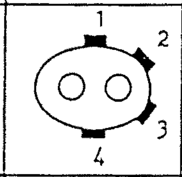
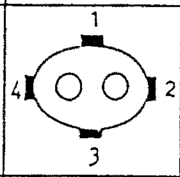
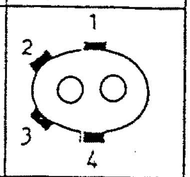
Experiment		No. 1	No. 2	No. 3	No. 4	No. 5	No. 6
Subject		T	T	Y	Y	K	K
electrode location							
discrimination rate (%)	proposed method	96	97	93	96	96	95
	AR model	92	99	87	94	90	94

Table 2. Function discrimination

	Experiment No. 1	Correct answer: Palmer flexion	Dorsi-flexion	Pronation	Supination	Grasp	Open	
Discrimination	Palmer flexion	46	0	0	0	0	0	
	Dorsi-flexion	0	44	0	0	0	0	
	Prona-tion	0	0	50	1	0	0	
	Supina-tion	0	0	0	48	0	0	
	Grasp	4	1	0	0	50	0	
	Open	0	5	0	1	0	50	Total
Correct answer (%)		92	88	100	96	100	100	96

for the EMG source in its off-diagonal element.

In contrast to the foregoing situation, when the electrodes are far away, the discrimination using only AR model (Nos. 1, 3 and 5) is lower by 4 to 7 percent than in the case where the electrodes are close. On the other hand, since the electrodes are far away, the amplitude patterns of EMG reflect well the different activities of the muscles in each motion. This implies that the discrimination by the discriminant function can complement the degradation of the discrimination rate by the AR model. Thus, the motion discrimination proposed in this paper can provide a larger degree of freedom in the electrode placement by utilizing the cross-information among electrode pairs as well as the frequency and amplitude characteristics of EMG.

5. Conclusions

The proposed method discriminates the motion by EMG, utilizing the amplitude of the prediction error of the multidimensional AR model and the pattern produced by electrode placement. The method has the feature that a larger degree of freedom is provided to the electrode placement, thereby reducing the complexity in electrode attachment.

It is decided from the result of experiment that the EMG for discrimination should be taken 100 ms after the onset of the motion. However, it is difficult to reduce the time for EMG observation further because of the nonstationarity of EMG. In the practical control of the prosthesis, the amputee performs a series of motions by switching various modes. The nonstationarity of EMG in switching the mode is inevitable. One of the interesting problems left for future study is to use the adaptive filter and similar ideas in the motion discrimination, considering the nonstationarity of EMG. The authors consider that the experiment of prosthesis control by the amputee, as well as the study of control system design including the proportional control by EMG for the discriminated motion, are necessary [2, 3].

Acknowledgement. The authors acknowledge the assistance made in this study by Mr. Y. Takahashi and Mr. K. Nakano (presently with Matsushita Corp.) of the Ergonomics Lab. of the Univ. A part of this study was supported by Sci. Grant., Min. Educ. (1985, No. 60550300) and a donation from the Mazda Foundation.

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 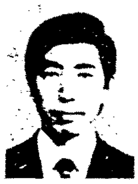 

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