

A Real-Time Pattern Recognition for Multifunction Myoelectric Hand Control

Jun-Uk Chu*, Inhyuk Moon*, and Museong Mun*

* Korea Orthopedics & Rehabilitation Engineering Center, Incheon, Korea
(Tel : +82-32-500-0576; E-mail: {juchu, ihmoon, msmun}@iris.korec.re.kr)

Abstract: This paper proposes a novel real-time EMG pattern recognition for the control of a multifunction myoelectric hand from four channel EMG signals. To cope with the nonstationary signal property of the EMG, features are extracted by wavelet packet transform. For dimensionality reduction and nonlinear mapping of the features, we also propose a linear-nonlinear feature projection composed of PCA and SOFM. The dimensionality reduction by PCA simplifies the structure of the classifier, and reduces processing time for the pattern recognition. The nonlinear mapping by SOFM transforms the PCA-reduced features to a new feature space with high class separability. Finally a multilayer neural network is employed as the pattern classifier. We implement a real-time control system for a multifunction virtual hand. From experimental results, we show that all processes, including virtual hand control, are completed within 125 msec, and the proposed method is applicable to real-time myoelectric hand control without an operation time delay.

Keywords: EMG, pattern recognition, linear-nonlinear feature projection, wavelet packet transform, PCA, SOFM.

1. INTRODUCTION

The myoelectric hand is an upper-limb prosthesis controlled by EMG signals taken from residual muscles of the amputee. It generally consists of three parts: a mechanical hand for performing finger and wrist functions, a surface electrode, and a controller. The EMG signal is essentially a one-dimensional pattern with a large variation and nonstationary properties. Therefore, most commercial myoelectric hands recognize user's intention by simply comparing the mean absolute value (MAV) of the EMG signal with a predetermined threshold [1, 2]. This is based on the fact that the amplitude of the EMG signal is almost proportional to the level of muscle activity [3]. However the simple comparison method using the MAV cannot be applied to a multifunction myoelectric hand with multi-DOFs because the MAV has only limited information based on amplitude. Consequently commercial myoelectric hands provide only a fewer hand functions, such as opening and grasping of the fingers, and pronation and supination of the wrist.

For a multifunction myoelectric hand, many studies have tried to extract a feature vector composed of separable and repeatable features from the EMG signal by using the time and frequency analysis. For example, the EMG amplitude, the zero-crossing rate [4, 5], the autoregressive coefficient [6], the Fourier transform coefficient [7], and the cepstrum coefficient [8] have been used as the components of the feature vector. However the pattern recognition results using these feature vectors have not had a high success rate because such methods assume that EMG signal is stationary.

Recently time-frequency analysis such as the short-time Fourier transform, the wavelet transform, and the wavelet packet transform have received considerable attention in the analysis of nonstationary signals because the time-frequency analysis produces a highly dimensional feature vector to provide more information. However the high dimensionality of the feature vector causes an increase in the learning parameters of the pattern classifier, and the convergence of the learning error deteriorates. Therefore, feature projection is essential for dimensionality reduction before applying the feature vector, extracted by time-frequency analysis, to the pattern classifier. Englehart et al. [9, 10] extracted a time-frequency feature vector by wavelet packet transform, and used principal component analysis (PCA) for dimensionality reduction. However, they could not show an effective result in recognition accuracy because PCA learning

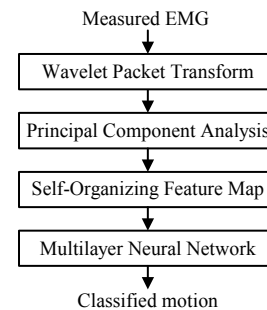


Fig. 1 Block diagram for EMG pattern recognition.

merely produces a well-described coordinate system for the distribution of all features, without consideration of the separation of class distribution. Although the PCA-reduced features have more than twenty dimensions and can approximate to the class distribution of the original features [10], a defect still exists in that the density functions of classes are not exactly discriminated.

To overcome this problem, we propose a new linear-nonlinear feature projection method composed of PCA and self-organizing feature map (SOFM), which includes two functions: dimensionality reduction and nonlinear mapping. Dimensionality reduction by PCA simplifies the structure of the classifier, and reduces processing time for pattern recognition. Nonlinear mapping by SOFM transforms the PCA-reduced features to a new feature space with improved class separability. As a result, the classifier can find a hyperplane with an enhanced separation margin. This scheme improves the recognition accuracy compared to using only PCA. In addition, it is applicable to real-time pattern recognition because it has a shorter processing time than that of directly applying time-frequency features to SOFM.

In this paper, we recognize nine kinds of hand motions from four channel EMG signals on the forearm using the proposed feature projection method, and control a virtual hand using the recognized results. To analyze the EMG signal with nonstationary properties, we first extract time-frequency features by a wavelet packet transform (see Fig. 1). The dimension of the wavelet packet feature is then reduced by PCA. Subsequently, SOFM transforms PCA outputs into a node of the lattice to build the clusters of feature sets. Finally, a multilayer neural network is employed as the classifier to recognize the hand motions.

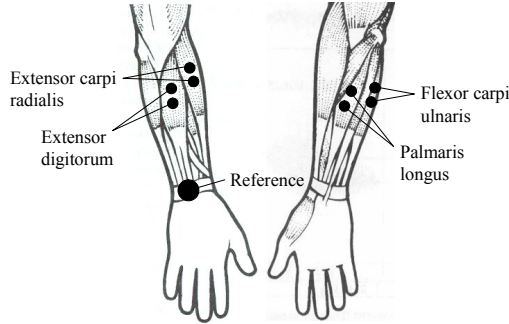


Fig. 2 Surface electrode placement on forearm muscles.

The ultimate objective of EMG pattern recognition in this study is to discriminate the user's intention in controlling the multifunction myoelectric hand. Therefore the response time of a myoelectric hand control system should be less than 300 msec, so that the user operates the hand without perceiving a time delay [11]. Accordingly, in this study we set a time constraint of 125 msec for the total processing time, including virtual hand control. We compare the proposed method with PCA and SOFM projection on the error rate and the processing time. From the comparison result, we show the proposed method is suitable for the purposes of controlling the myoelectric hand, because the method achieves a real-time process with a high recognition accuracy, similar to that of the SOFM method. Using the method, we implemented a real-time control system for a virtual hand, and we show that the virtual hand is controlled within 300 msec.

2. EMG ACQUISITION

In this paper, we try to recognize nine kinds of hand motion; flexion and extension of the wrist, radial and ulnar flexion of wrist, pronation and supination of wrist, opening and grasping of the fingers, and relaxation. Since hand motions result from contraction of the muscles in the forearm, we use four surface electrodes for measuring EMG signals from the extensor digitorum, the extensor carpi radialis, the palmaris longus, and the flexor carpi ulnaris, which are the muscles concerned with hand motion (see Fig. 2 [12]).

Generally, the frequency range of EMG is within 0 to 2000 Hz, but the dominant energy is concentrated in the range 20 to 500 Hz, and its amplitude is limited to 0 to 10 mV [13]. Therefore we used an active surface electrode (DE-2.1, DELSYS) with a bandpass filter of 10 to 450 Hz bandwidth and an amplifier with 100 dB gain. The EMG signals were digitized by an ADC board (6052E, NI). The sampling frequency was 1024 Hz. The digitized EMG signals are first segmented by a moving window, and then features for the pattern recognition are extracted from the segmented signals by the wavelet packet transform. We set the length of moving window to 250 msec (256 samples) and the window increment to 125 msec (128 samples).

3. EMG PATTERN RECOGNITION

3.1 Wavelet packet transform

To extract a feature vector from EMG signals, we use a wavelet packet transform that is a generalized version of the wavelet transform. A signal with N points is decomposed into an overcomplete set of subspaces with different time-frequency localization characteristics. The root node $\Omega_{0,0}$ is the original signal space. A subspace $\Omega_{j,k}$ is

decomposed into two orthogonal subspace $\Omega_{j,k} \rightarrow \Omega_{j+1,2k}$ and $\Omega_{j,k} \rightarrow \Omega_{j+1,2k+1}$. Here j denotes scale and k indicates the subband index within the scale. Each subspace $\Omega_{j,k}$ is spanned by basis vectors

$\{w_{j,k,n}\}$, $n=0, \dots, 2^{n_0-j}-1$, where $n_0 = \log_2 N$. This means that the complete basis of the time-frequency plane may take many forms according to the selected the partitions of the frequency axis. For the pattern recognition task, if we introduce a proper discriminant measure, the best basis can be chosen to maximize the class separability specified by a discriminant measure. To determine the best basis, we use the local discriminant basis (LDB) algorithm proposed by Saito and Coifman [14]. The symmetric relative entropy as a discriminant measure is chosen as

$$D(\mathbf{p}, \mathbf{q}) = \sum_{i=1}^n p_i \log \frac{p_i}{q_i} + \sum_{i=1}^n q_i \log \frac{q_i}{p_i} \quad (1)$$

where $\mathbf{p} = \{p_i\}$, $\mathbf{q} = \{q_i\}$, $i=1, \dots, n$ are measures used to represent the features from two different classes. For input parameters to the symmetric relative entropy, the time-frequency energy map of each class is defined as

$$\Gamma_c(j, k, n) = \sum_{i=1}^{N_c} (\mathbf{w}_{j,k,n}^T \mathbf{x}_i^{(c)})^2 / \sum_{i=1}^{N_c} \|\mathbf{x}_i^{(c)}\|^2 \quad (2)$$

where $j=0, \dots, J$, $k=0, \dots, 2^j-1$, and $n=0, \dots, 2^{n_0-j}-1$. $\{\mathbf{x}_i^{(c)}\}$, $i=1, \dots, N_c$ is a set of training signals belonging to class c , where N_c is the number of patterns in class c . Combining (1) with (2), the symmetric relative entropy of the subspace $\Omega_{j,k}$ for K classes is written as

$$D(\{\Gamma_c(j, k, \bullet)\}_{c=1}^K) = \sum_{n=0}^{2^{n_0-j}-1} D(\Gamma_1(j, k, n), \dots, \Gamma_K(j, k, n)) \quad (3)$$

The LDB algorithm locally performs a comparison between a parent node (j, k) and the children nodes $\{(j+1, 2k), (j+1, 2k+1)\}$, and helps us to keep the parent node or to sink deeper toward the children nodes. To recognize nine hand motions, we first calculate the energy maps of the nine motion classes in each subspace, and then the LDB is constructed by comparing the symmetric relative entropy to the other nodes. To increase the class separability, we independently construct the LDB for each channel. Based on four sets of the LDB, the wavelet packet transform coefficients are obtained, and their absolute values are extracted as features in the pattern recognition procedure.

3.2 Feature projection

Once the absolute values of the wavelet packet transform coefficients are extracted as features, then PCA performs the dimensionality reduction of the features. The recognition performance is sensitive to the dimensionality reduction of the feature vector, but it is not affected by the dimensionality reduction if the PCA-reduced dimension is more than twenty orders [10]. As we take a feature vector with five orders from each of the four channels, the feature vector becomes twenty orders in total. The learning procedure of PCA is a process for establishing a well-described coordinate system for the distribution of input features. Further, PCA has the advantages of having a closed-form solution and of automatically ranking the importance of the features in the projection space.

The SOFM nonlinearly transforms the PCA-reduced features into a new feature space with high class separability. In this study the SOFM is prepared independently for each channel. The input layer of each SOFM is composed of five outputs from the PCA, and its output layer forms a 40×40 two dimensional lattice. In the learning procedure of SOFM, the synaptic weight vectors are adjusted based on the similarity to the input pattern and the topological neighborhood of the winning neuron. The best-matching (winning) neuron $i(\mathbf{x})$ at time step n is determined by using the minimum-distance Euclidean criterion:

$$i(\mathbf{x}) = \arg \min_j \|\mathbf{x}(n) - \mathbf{w}_j\| \quad (4)$$

where $j=1, \dots, l$ and l is the number of neurons in the lattice. The synaptic weight vectors of all neurons are adjusted by using the update formula

$$\mathbf{w}_j(n+1) = \mathbf{w}_j(n) + \eta(n) h_{j,i(\mathbf{x})}(n) (\mathbf{x}(n) - \mathbf{w}_j(n)) \quad (5)$$

where $\eta(n)$ is the learning rate, and $h_{j,i(\mathbf{x})}(n)$ is the neighborhood function centered around the winning neuron $i(\mathbf{x})$. The topological neighborhood assumes a time-varying form of its own, as shown by

$$h_{j,i(\mathbf{x})} = \exp\left(-d_{j,i}^2 / 2\sigma^2(n)\right) \quad (6)$$

where $d_{j,i}$ is the lateral distance between the winning neuron i and the excited neuron j in the two-dimensional lattice. A popular choice for the dependence of width σ on discrete time n is the exponential decay described by

$$\sigma(n) = \sigma_0 \exp(-n/\tau_1) \quad (7)$$

where σ_0 is the value of σ at the initiation of the SOFM algorithm, and τ_1 is a time constant. Also, the learning rate $\eta(n)$ should be time varying. It should start at an initial value η_0 , and then decrease exponentially with increasing time n , as shown by

$$\eta(n) = \eta_0 \exp(-n/\tau_2) \quad (8)$$

where τ_2 is another time constant of SOFM algorithm. To classify the same pattern data within a class to the same pattern cluster, the weight vectors for the SOFM are initialized from the set of input patterns in a random manner, and all patterns in each class are fairly selected in the sampling process. In the pattern recognition procedure, the SOFM finds the winning neuron with the best similarity between its weight vector and the input pattern. Then, the two-dimensional coordinates of the winning neuron is the components of the feature vector.

3.3 Pattern classification

Finally, a multilayer neural network with two hidden layers is employed as the pattern classifier. Using the cascaded architecture of PCA and SOFM, a feature vector of each channel with high dimensionality is mapped into a node in a two-dimensional lattice. Consequently, the input layer of the multilayer neural network is constructed from the eight outputs of the SOFMs and its output layer has nine neurons for the nine hand motions to be recognized. A bipolar sigmoid function $f(v) = 2/(1+e^{-v}) - 1$ is used as an activation function. For error back-propagation learning, we prepare training samples $\{\mathbf{x}(n), \mathbf{d}(n)\}$, $n=1, \dots, N$, where $\mathbf{x}(n)$ is the input pattern, and $\mathbf{d}(n)$ is the desired output vector at iteration

PC and A/D card Graphic user interface

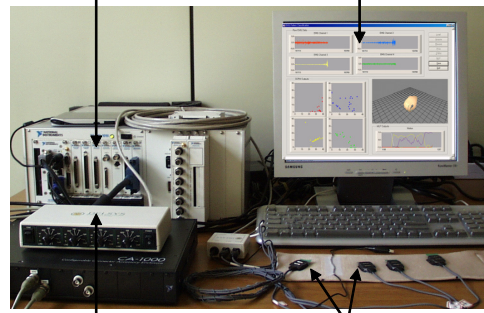


Fig. 3 Experimental setup.

n . According to the hand motion, the element of the desired output vector, $d_i(n)$, is set to $+1$, otherwise -1 . The error signal at the output of neuron i at the iteration n is defined by $e_i(n) = d_i(n) - y_i(n)$. According to the generalized delta rule and the chain rule, the synaptic weights and the bias are adjusted.

4. EXPERIMENTAL RESULTS

The ultimate objective of EMG pattern recognition in this study is to discriminate the user's intention in controlling the myoelectric hand. For this application the response time of a myoelectric hand control system should be less than 300 msec, so that the user does not perceive an operation delay. To satisfy this condition, we set the length of moving window to 250 msec and the window increment to 125 msec. That is, we make two sequential windows contain the same data in the overlapped interval. If the total processing time, including the hand control, is less than 125 msec, the myoelectric hand can respond to the user's intention within 300 msec.

In this section, we explain the learning procedure of the proposed method, and we compare the method with PCA and SOFM projection on the error rate and the processing time. We implemented a real-time control system for a multifunction virtual hand, and we show that the virtual hand is controlled within 300 msec. Figure 3 shows the experimental setup including four surface electrodes, amplifier and filter system, a PC with A/D board, and a graphical user interface. In experiments, the subject alternately and sequentially performed nine hand motions including relaxation for a period of about ninety seconds, and EMG signals were measured at the same time. The measured dataset from the first 45056 msec was used for the learning procedures, and the second dataset with a duration of 46848 msec was used for the evaluation of recognition performance.

4.1 Learning procedures

In the learning procedures, the full dataset is split into a subsets of 256 samples, and each subset is labeled as a class corresponding to a hand motion. The subset increases by 128 samples every processing. The parameters to be found in the learning procedure for pattern recognition are summarized as follows:

1. LDB for wavelet packet transform.
2. Eigenvectors of the covariance matrix for PCA.
3. Weight vectors of SOFM.
4. Weight vectors of multilayer neural network.

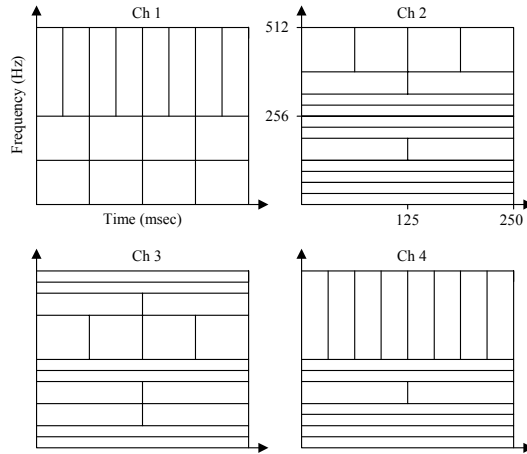


Fig. 4 The tiling of the selected subspaces in the time-frequency plane for each channel.

In the LDB algorithm, discrete wavelet decomposition was implemented using the Mallat algorithm [15]. We specified the depth of decomposition level as four, and used the Symmlet wavelet and scaling function of five orders having ten coefficients. The filtering and down-sampling operations with these coefficients produced various dimensions of basis vectors for decomposition levels. Figure 4 illustrates the tilings of the selected subspaces in the time-frequency plane for each channel. As a result, the LDB algorithm constructed an independent time-frequency plane for each channel to maximize the class separability in contrast to the fixed tiling of the wavelet transform. The features for the pattern recognition procedure are then extracted by wavelet decomposition according to the set of the LDB.

In the PCA learning procedure, we first constructed the covariance matrix from the absolute values of the wavelet packet transform coefficients. Since the PCA-reduced feature vector with twenty orders can approximate the class distribution of original features, we selected five eigenvectors corresponding to the largest eigenvalues from each channel as the PCA projection matrix used for the dimensionality reduction. Figure 5 shows the selected two principal components from the PCA-reduced feature vector with five orders. As shown in Fig. 5, the separability between classes is low because the density functions of pattern classes are overlapped due to the effect of signal compression by the PCA projection.

In the SOFM learning procedure, the initial weight vectors were randomly selected from the PCA-reduced feature vector. In (7), the initial width of the neighborhood functions was set to $\sigma_0 = 20$ in order to cover the 40×40 lattice space, and the time constant was set to $\tau_1 = 2000$. The learning rate and the time constant in (8) were initialized to $\eta_0 = 0.9$ and $\tau_2 = 2000$, respectively. As the result of the SOFM learning, the weight vectors were converged after 4000 iterations. Figure 6 depicts nonlinearly clustered classes in the lattice of the SOFM. We can see that the patterns belonging to the same class are well clustered, and the class separability is vastly improved compared to the PCA projection.

In this study we used the multilayer neural network as the classifier. The number of hidden layer was two, and each hidden layer had nine neurons. The input of the neural network was the normalized value of the SOFM outputs, and we chose the weights and bias from a uniform distribution whose mean and variance were zero and one, respectively. The

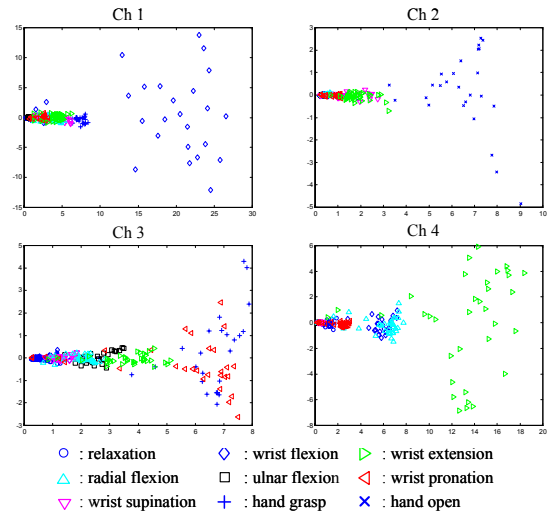


Fig. 5 Two principal components of the PCA-reduced features.

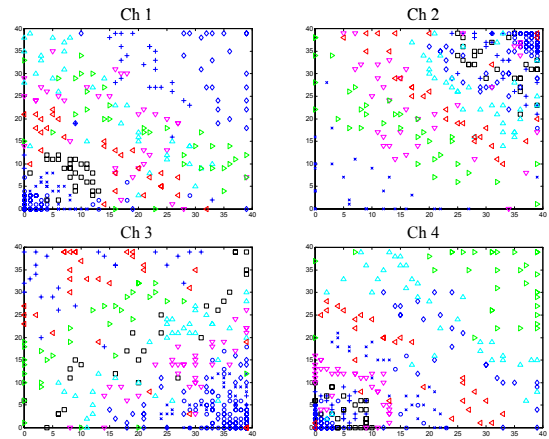


Fig. 6 Clustered classes in the lattice by SOFM.

learning rate was set to 0.1, and the learning process was stopped when the absolute rate of change in the average squared error per epoch was sufficiently small.

4.2 Evaluation of the proposed method

Having determined the parameters of LDB, PCA, SOFM, and multilayer neural network in the learning procedure, we evaluated the recognition accuracy of the proposed method using the test dataset. Figure 7 shows the EMG test dataset with a duration of 46848 msec and the recognized results are shown at the bottom of Fig. 7. To evaluate the recognition performance, each motion was assigned to the numbers 0 to 8, and the outputs of the multilayer neural network were then compared with the desired output corresponding to the hand motion. The open circle drawn in the recognized results denotes the maximum output of the multilayer neural network and the solid line indicates the desired output. The experimental results show high accuracy with the exception of the motion transition state.

Using the same test dataset, we compared our method with the PCA and SOFM projection. Figure 8 shows the error rates, where 'PCA+SOFM', 'SOFM', and 'PCA' denote each projection method used in pattern recognition, respectively. From this result, we can see 'PCA' has a higher error rate because the PCA transforms the wavelet packet feature to a new feature space with the maximum distribution of all

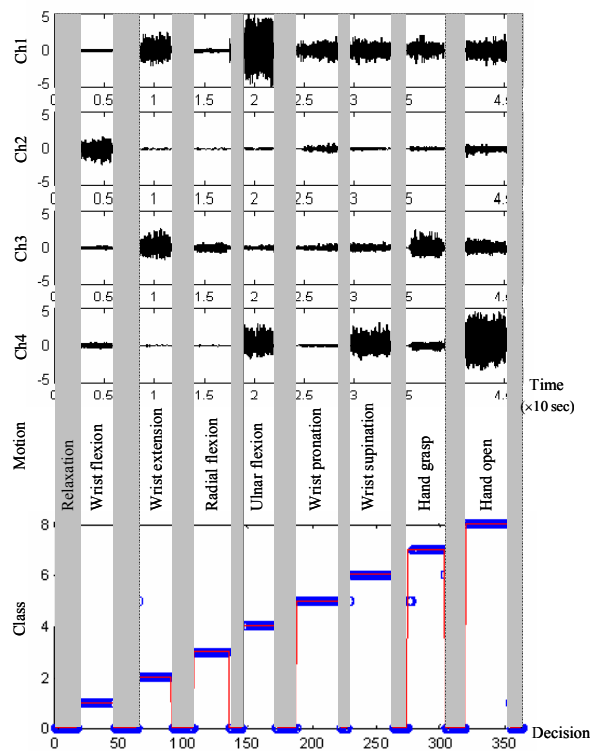


Fig. 7 Test patterns and recognized results.

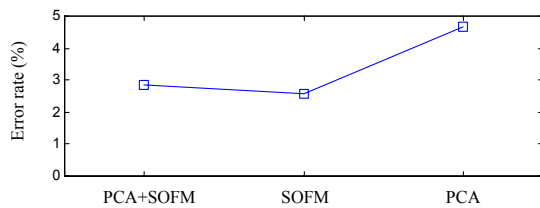


Fig. 8 Error rates.

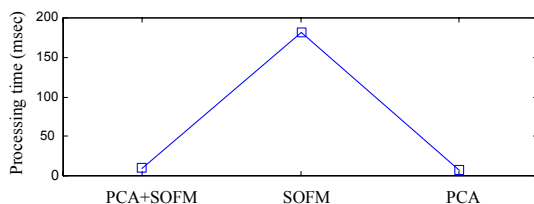


Fig. 9 Processing time taken for feature projection.

features. This means that the PCA-reduced features have a low separability. On the other hand, the ‘SOFM’ achieved the best pattern recognition because the feature vectors are nonlinearly transformed into a new feature space with an enhanced separation margin. However the SOFM needed much more processing time as shown in Fig. 9, because the raw feature vector with high dimensionality was directly used in the nonlinear mapping. To implement a real-time pattern recognition, the processing time should be less than the window increments, 125 msec. Accordingly the SOFM method is inadequate for real-time processing. The evaluation results in Fig. 8 and 9 show that the proposed method was suitable for myoelectric hand control, because it could achieve real-time pattern recognition with high accuracy.

4.3 Real-time multifunction myoelectric hand control

Using the proposed EMG pattern recognition method, we implemented a real-time control system for a three

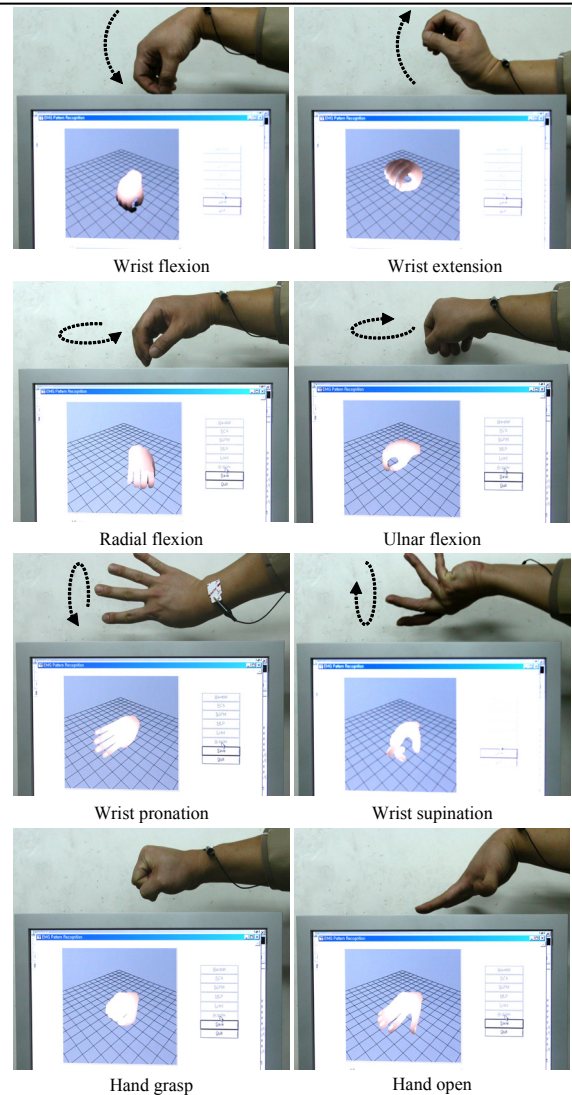


Fig. 10 Virtual hand controlled by real-time EMG pattern recognition.

dimensional virtual hand, graphically designed using OpenGL. In this experiment, the control system was executed on a 1.8 GHz Pentium IV PC. Figure 10 shows the virtual hand controlled by the EMG signals. In this figure, the dashed lines indicate the directions of motion, and the virtual hand shows the final postures controlled. For example, we explain the recognition procedure of ulnar flexion. When the user makes an ulnar flexion, stronger EMG signals were measured in channels 1 and 4 than in channels 2 and 3. Figure 11 shows EMG signals in the transient state from relaxation to ulnar flexion. The recognized results are shown in the lower part of Fig. 11. The square and circle denote the outputs of the multilayer neural network assigned to the relaxation and the ulnar flexion, respectively. These outputs were generated every 125 msec. This interval is the same as the increment of the data window. First, the user’s intention to make ulnar flexion was given at time ①. The ulnar flexion, however, could not be recognized at time ② because the pattern recognition was performed using the data sampled at the previous step not including time ①. After 125 msec, the data window was increased, and the ulnar flexion was recognized at time ③ correctly. Finally, the virtual hand was controlled. Since we implemented the virtual hand using OpenGL, the

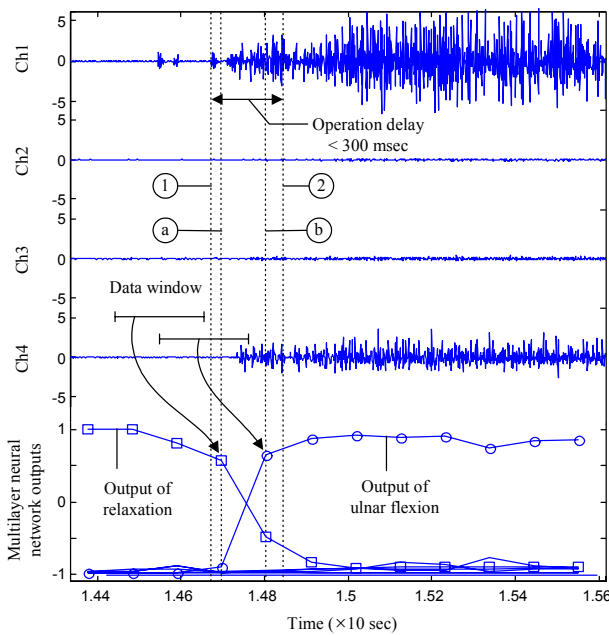


Fig. 11 Transient state from relaxation to ulnar flexion.

Table 1. Average processing time in real-time pattern recognition.

Processes	Average Time [msec]
Wavelet packet transform	30
PCA + SOFM	5
Multilayer neural network	5
Virtual hand control	40
Overheads	20
Total processes	100

three dimensional graphics needed about 40 msec processing time. Therefore, the virtual hand control was competed at time ②. Table 1 shows that the total processing time was less than 125 msec. This result shows that the operation delay is less than 300 msec, and the proposed method is applicable to the control of a multifunction myoelectric hand in real-time.

5. CONCLUSIONS

This paper proposed a real-time EMG pattern recognition using linear-nonlinear feature projection for a multifunction myoelectric hand. The proposed linear-nonlinear feature projection method was composed of PCA and SOFM, which performed dimensionality reduction and nonlinear mapping. To analyze the EMG with nonstationary signal properties, a time-frequency feature vector was extracted by the wavelet packet transform. The dimension of the wavelet packet features was then reduced by PCA. Subsequently SOFM nonlinearly transformed the PCA-reduced feature to a new feature space with improved class separability. As a result, the multilayer neural network could find a hyperplane with an enhanced separation margin. Using the proposed method, we tried to recognize nine kinds of motion from four channel EMG signals and control the virtual hand in real-time. From the experimental results, we showed that all processes including hand control were completed within 125 msec, and that the proposed method is applicable for real-time myoelectric hand control without a perceived operation time delay. In the future, we will test the validity by applying the

proposed method to a multifunction myoelectric hand with 4 DOFs developing.

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