A Real-Time EMG Pattern Recognition System Based on Linear-Nonlinear Feature Projection for a Multifunction Myoelectric Hand

Jun-Uk Chu, *Member, IEEE*, Inhyuk Moon*, *Member, IEEE*, and Mu-Seong Mun

***Abstract*—This paper proposes a novel real-time electromyogram (EMG) pattern recognition for the control of a multifunction myoelectric hand from four channel EMG signals. To extract a feature vector from the EMG signal, we use a wavelet packet transform that is a generalized version of wavelet transform. For dimensionality reduction and nonlinear mapping of the features, we also propose a linear-nonlinear feature projection composed of principal components analysis (PCA) and a self-organizing feature map (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 into a new feature space with high class separability. Finally, a multilayer perceptron (MLP) is used as the classifier. Using an analysis of class separability by feature projections, we show that the recognition accuracy depends more on the class separability of the projected features than on the MLP's class separation ability. Consequently, the proposed linear-nonlinear projection method improves class separability and recognition accuracy. We implement a real-time control system for a multifunction virtual hand. Our experimental results show that all processes, including virtual hand control, are completed within 125 ms, and the proposed method is applicable to real-time myoelectric hand control without an operational time delay.**

***Index Terms*—EMG, linear-nonlinear feature projection, pattern recognition, principal components analysis, self-organizing feature map, wavelet packet transform.**

I. Introduction

A myoelectric hand is an upper-limb prosthesis controlled by electromyogram (EMG) signals taken from residual muscles of a limb-deficient individual. In recent years, several multifunction myoelectric hands have been developed [1]–[3]. These hands have a number of degrees of freedom and dexterous hand functions. Such a multifunction myoelectric hand requires a robust and computationally efficient control strategy. As one means of accomplishing this, pattern recognition based control schemes have been suggested [4]–[7]. These studies have tried to extract a feature vector composed of separable and repeatable features from the EMG signal by using time and frequency analysis. For example, the EMG amplitude, the zero-crossing rate [4], autoregressive coefficients [5], Fourier transform coefficients [6], and cepstrum coefficients [7] have been used as the components of the feature vector.

Recently, time-frequency analysis, such as short-time Fourier transform, wavelet transform, and wavelet packet transform have received considerable attention in the analysis of nonstationary signals. Time-frequency analysis offers a map of the temporal localization of a signal's spectral characteristics in the time-frequency domain, but it yields a high-dimensional feature vector. Generally, the high dimensionality of a feature vector causes an increase in the learning parameters of a classifier. Thus, it requires dimensionality reduction of the feature vector without loss of classification accuracy. Dimensionality reduction increases classifier speed and reduces its memory requirements [8]. In time-frequency analysis, feature projection for dimensionality reduction is essential before applying the feature vector to a classifier. Englehart *et al.* [9], [10] extracted a time-frequency feature vector through wavelet packet transform and used principal components analysis (PCA), a linear feature projection method for dimensionality reduction. The PCA-reduced features can approximate the distribution of the original features, but a defect still exists in that the clusters for different classes are not exactly separated in the reduced feature space. The reason is that PCA learning merely produces a well-described coordinate system for the distribution of all features, without consideration of the class separation. It is known that features with high class separability improve recognition accuracy. In this work, an additional nonlinear mapping of the linear-projected feature vector yields a new feature vector with improved class separability.

We propose a new linear-nonlinear feature projection method composed of PCA and a 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

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J.-U. Chu and M.-S. Mun are with Korea Orthopedics and Rehabilitation Engineering Center, Incheon 403-712, Korea.

*I. Moon was with Korea Orthopedics and Rehabilitation Engineering Center, Incheon 403–712, Korea. He is now with the Department of Mechatronics Engineering, Dong-Eui University, Busan 614-052, Korea (e-mail: ihmoon@deu.ac.kr).

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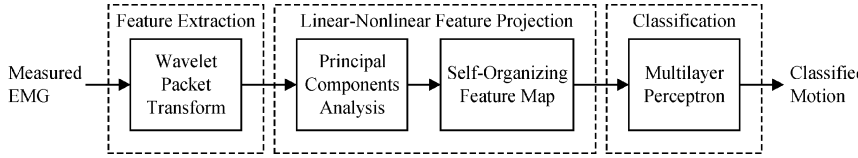

Fig. 1. Block diagram for EMG pattern recognition.

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 motion from four channel EMG signals on the forearm using the proposed feature projection method, and control a virtual hand using the recognized results. We first extract a feature vector by 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 perceptron (MLP) is used as the classifier to recognize the hand motions.

The MLP has abilities of both a nonlinear discriminant analysis (NLDA) and a nonlinear classifier [11]. Although MLP has the ability of NLDA for nonlinear mapping, the recognition accuracy highly depends on class separability of the input feature. In Section IV, we clarify that the additional nonlinear mapping by SOFM affects the recognition accuracy, in a manner than complements the MLP's class separation ability.

The ultimate objective of EMG pattern recognition in this paper 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 ms, so that the user operates the hand without perceiving a time delay [12]. In experiments, we compare the proposed method with PCA and SOFM projection with regard to the classification success rate and the processing time, and we implement a real-time control system for a virtual hand based on the proposed method. Our experimental results show that the virtual hand is actuated within 300 ms and that the proposed method is suitable for the purposes of controlling a myoelectric hand in real time.

II. Experiments and Data Acquisition

In this paper, we try to recognize nine kinds of hand motion: flexion and extension of the wrist, radial and ulnar flexion of the wrist, pronation and supination of the wrist, opening and grasping of the fingers, and relaxation. Because 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 motions.

Generally, the frequency range of EMG is within 0–1000 Hz, but the dominant energy is concentrated in the range of 20–500 Hz, and its amplitude is limited to 0–10 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.[1] The EMG signals were digitized by an analog-to-digital board (6052E, NI).[2] The sampling frequency was 1024 Hz.

[1]Available online at http://www.delsys.com.

[2]Available online at http://www.ni.com.

In experiment, EMG data were collected from ten normally subjects (six males and four females, 31 ± 4.3 yrs.). Each subject performed nine hand motions including relaxation and conducted 20 sessions. The first ten sessions were used for the learning procedures, and the remaining ten sessions were used for the evaluation of recognition performance. In each session, each motion was performed once for a duration of about 4 s and switched between relaxation and static contraction.

The response time of a myoelectric hand control system should be less than 300 ms, so that the user operates the hand without perceiving a time delay [12]. We apply a moving window scheme with a window increment to recognize a steady-state motion. Although a small window increment improves the response time of the myoelectric hand, the window increment is determined by considering the processing time of the pattern recognition algorithm. For real-time implementation, all processes, including hand control, must be completed within the window increment. In this paper, we set the length of the moving window to 250 ms (256 samples) with a 125 ms (128 samples) window increment. Consequently, this scheme generates two decisions within 300 ms. This guarantees that the user can control a directed myoelectric hand function within 250 ms from the instant when the user's intention is given.

III. Algorithm Description

A. Feature Extraction

To extract a feature vector from EMG signals, we use a wavelet packet transform that is a generalized version of wavelet transform. The complete basis of the time-frequency plane may take many forms according to the selected 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 the discriminant measure. To determine the best basis, we use the local discriminant basis (LDB) algorithm proposed by Saito and Coifman [14]. We first calculate the time-frequency energy maps of class c, $\Gamma_c(j,k,n)$, where j and k denote the scale and the subband index within the scale, respectively and $n = 0, \ldots, 2^{n_0 - j} - 1$, where $n_0 = \log_2^N$ and N is the number of points in the data window. To measure class separability, we use the energy maps as inputs to the symmetric relative entropy. The symmetric relative entropy of the subspace (j,k) for K classes is written as

$$D(\{\Gamma_c(j,k,\bullet)\}_{c=1}^{K}) = \sum_{a=1}^{K-1} \sum_{b=a+1}^{K} D(\Gamma_a(j,k,n), \Gamma_b(j,k,n)) \tag{1}$$

where

$$D(\Gamma_a(j,k,n),\Gamma_b(j,k,n)) = \sum_{n=0}^{2^{n_0-j}-1} \times \left\{ \Gamma_a(j,k,n)\log\frac{\Gamma_a(j,k,n)}{\Gamma_b(j,k,n)} + \Gamma_b(j,k,n)\log\frac{\Gamma_b(j,k,n)}{\Gamma_a(j,k,n)} \right\}.$$

The LDB is then constructed by the pruning method. A detailed description of the LDB algorithm was given in [10]. To increase the class separability, we independently construct the LDB for each channel. Based on four sets of the LDB, the WPT coefficients are obtained, and their absolute values are extracted as features in the pattern recognition procedure.

It is noted that EMG signals are stationary when the subjects perform static contractions, and the majority of the windows include static contractions. This means that, in steady-state motion, WPT coefficients do not have the temporal information of the time-frequency plane. Nevertheless, WPT features are superior to time and frequency features, such as EMG amplitude and Fourier transform coefficients because the wavelet functions resemble the motor unit action potentials that constitute the gross EMG signal [10], and the wavelet transform represents the EMG signal by the sum of the scaled and shifted versions of wavelet function.

B. Feature Projection

Once the absolute values of the WPT coefficients are extracted as features, PCA performs the dimensionality reduction for each channel. 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]. Because we take a feature vector with five orders from each of the four channels, the feature vector becomes 20 orders in total. The learning procedure of the PCA is a process for establishing a well-described coordinate system for the distribution of input features. Furthermore, PCA has the advantages of a closed-form solution and automatically ranking the importance of the features in the projection space [15].

The SOFM nonlinearly transforms the PCA-reduced features into a new feature space with high class separability. In this paper, 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 (2-D) lattice in consideration of processing time and feature map resolution. In the learning procedure of the SOFM, the synaptic weight vectors are adjusted based on their similarity to the input feature and the topological neighborhood of the winning neuron. To train feature vectors within the same class to cluster, the weight vectors for the SOFM are initialized from the set of input features in a random manner, and all features in each class are fairly selected in the sampling process. The learning procedure for the SOFM applied in this paper is as follows [16].

1) Select the initial weight vectors $\mathbf{w}_j(0)$ from the available set of input features in a random manner, where $j = 1, \ldots, l$ and l is the number of neurons in the lattice.
2) Choose a feature $\mathbf{x}$ from each class with a certain probability.
3) Find the best-matching (winning) neuron $i(\mathbf{x})$ at time step n by using the minimum-distance Euclidean criterion

$$i(\mathbf{x}) = \arg\min_j \|\mathbf{x}(n) - \mathbf{w}_j\|, j = 1, \ldots, l. \tag{2}$$

4) Adjust the synaptic weight vectors of all neurons by using the update formula

$$\mathbf{w}_j(n+1) = \mathbf{w}_j(n) + \eta(n)h_{j,i(\mathbf{x})}(n)(\mathbf{x}(n) - \mathbf{w}_j(n)) \tag{3}$$

where $\eta(n)$ is the learning rate and $h_{j,i(\mathbf{x})}(n)$ is the neighborhood function centered around the winning neuron $i(\mathbf{x})$; for best results, both $\eta(n)$ and $h_{j,i(\mathbf{x})}(n)$ are varied dynamically during learning.
5) Continue with Step 2 until no noticeable changes in the feature map are observed.

In Step 4, the topological neighborhood assumes a time-varying form of its own, as shown by

$$h_{j,i(\mathbf{x})} = \exp\left(\frac{-d_{j,i}^2}{2\sigma^2(n)}\right) \tag{4}$$

where $d_{j,i}$ is the lateral distance between the winning neuron i and the excited neuron j in the 2-D lattice. A popular choice for the dependence of width σ on discrete time n is the exponential decay described by

$$\sigma(n) = \sigma_0 \exp\left(\frac{-n}{\tau_1}\right) \tag{5}$$

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

$$\eta(n) = \eta_0 \exp\left(\frac{-n}{\tau_2}\right) \tag{6}$$

where τ_2 is another time constant of the SOFM algorithm. In the pattern recognition procedure, the SOFM finds the winning neuron with the best similarity between its weight vector and the input feature. Then, the 2-D coordinates of the winning neuron are the components of the feature vector.

C. Classification

Finally, an MLP is used as the classifier. The number of hidden layers is two, and each hidden layer has nine neurons. We determined the network structure by trial and error. The selection criterion is based on the convergence of learning error. Using the cascaded architecture of PCA and SOFM as shown in Fig. 1, a feature vector of each channel with high dimensionality is mapped into a node in a 2-D lattice. Consequently, the

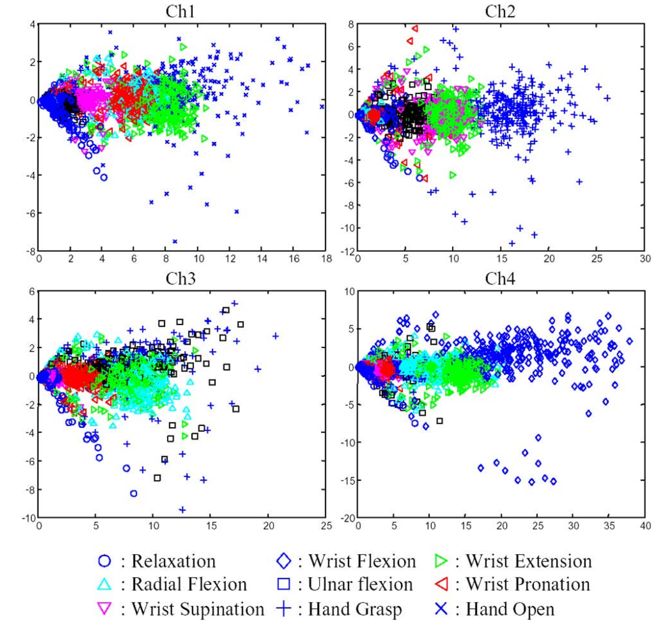

Fig. 2. Two principal components of the PCA-reduced features.

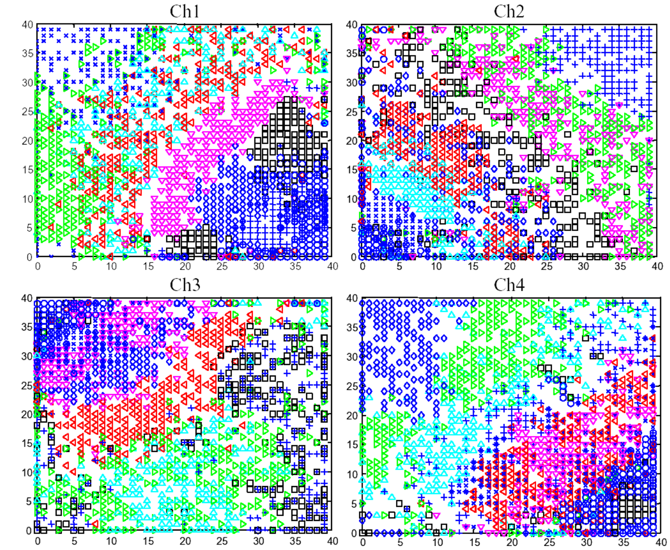

Fig. 3. Clustered features in the lattice by SOFM.

input layer of the MLP is constructed from the eight outputs of the SOFM for four channels, and its output layer has nine neurons for the nine hand motions to be recognized. We select the maximum output of the MLP as the recognized motion.

D. Learning Procedure

In this subsection, we describe the learning procedure of the proposed method. For the learning procedure, the full dataset is split into subsets of 256 samples, with the increment of 128 samples. Each subset is labeled as a member of a class corresponding to the hand motion. The parameters to be found in the learning procedure are summarized as follows:

1) local discriminant basis for WPT;
2) eigenvectors of the covariance matrix for PCA;
3) weight vectors of SOFM;
4) weight vectors of MLP.

In the LDB algorithm, discrete wavelet decomposition was implemented using the Mallat algorithm [17]. 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. 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. According to the set of the LDB, the WPT coefficients are obtained by wavelet decomposition, and their absolute values are extracted as features in the pattern recognition procedure.

In the PCA learning procedure, we first constructed the covariance matrix from the absolute values of the WPT coefficients. Because the PCA-reduced feature vector with 20 orders can approximate the class distribution of the original features, we selected five eigenvectors corresponding to the largest eigenvalues from each channel as the PCA projection matrix used for the dimensionality reduction. Fig. 2 shows, from a typical data record, the two selected principal components from the PCA-reduced feature vector with five orders. As shown in Fig. 2, the separability between classes is low because the clusters for different classes overlap 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 (5), the initial width of the neighborhood functions was set to $\sigma_0 = 20$ 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 (6) were initialized to $\eta_0 = 0.9$ and $\tau_2 = 2000$, respectively. In SOFM learning, the weight vectors converged after 4000 iterations. Fig. 3 depicts nonlinearly clustered features in the lattice of the SOFM. We can see that the features belonging to the same class are well clustered, and the class separability is improved compared to the PCA projection.

In the MLP learning procedure, the inputs of the MLP were the normalized values of the SOFM outputs, and a bipolar sigmoid function was used as an activation function. For error backpropagation learning, we chose the initial weights and bias from a uniform distribution whose mean and variance were zero and one, respectively. The 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 iteration was sufficiently small.

IV. Experimental Results

A. Evaluation of the Proposed Method

Having determined the parameters of the LDB, PCA, SOFM, and MLP in the learning procedure, we evaluated the recognition accuracy of the proposed method using a test session. Fig. 4 shows the test session and the recognized results by the proposed projection method and PCA projection only. The EMG signals in Fig. 4(a) are typical data recorded from a typical subject. The top of Fig. 4(b) shows MLP output values between -1.0 and 1.0. The maximum output is selected as the recognized motion in every decision. The bottom of Fig. 4(b) shows the recognized results, in which each motion is assigned to the numbers 0 to

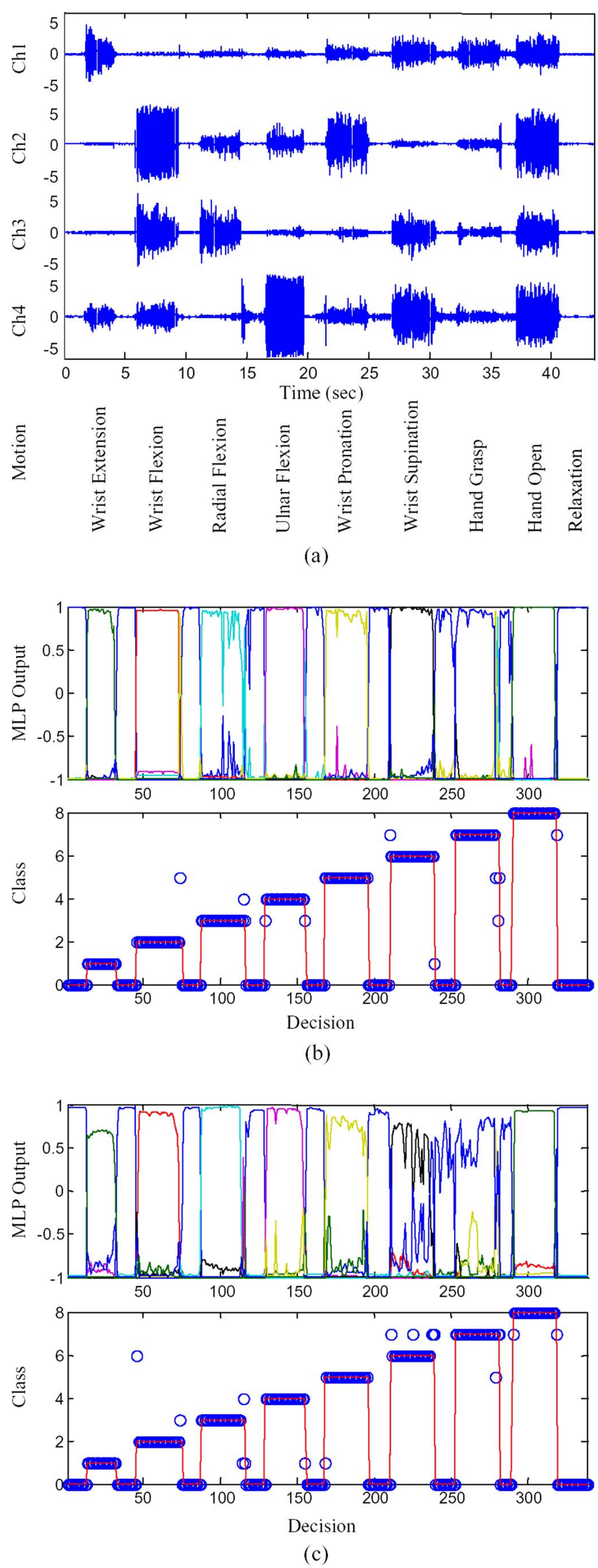

Fig. 4. Test session and recognition results: (a) test session; (b) results by the linear-nonlinear projection; (c) results by the PCA projection only.

TABLE I
CLASSIFICATION SUCCESS RATE FOR FEATURE PROJECTION METHODS

Subject	PCA + SOFM	SOFM	PCA
1	94.17	95.21	94.12
2	96.55	97.85	95.23
3	97.83	98.58	96.64
4	96.79	96.85	95.07
5	97.88	98.64	95.95
6	96.44	98.12	95.54
7	98.63	98.68	98.08
8	98.34	98.50	97.65
9	94.97	96.58	93.17
10	98.64	98.84	96.14
Mean	97.024	97.785	95.759

TABLE II
PROCESSING TIME FOR FEATURE PROJECTION METHODS

Processes	Processing time (msec)
PCA + SOFM	5
SOFM	180
PCA	2

8. The solid line and open circle denote the desired output and recognized motion, respectively. The results by the proposed method show high accuracy with the exception of transient-state motions; the MLP outputs are stable in steady-state motions. Contrarily, the results by PCA projection have a slightly higher occurrence of errors in steady-state motion, which is caused by unstable MLP outputs as shown in Fig. 4(c).

We evaluated the performance of pattern recognition for ten subjects. Table I lists the averaged classification success rate, where "PCA+SOFM," "SOFM," and "PCA" denote each projection method used in pattern recognition, respectively. To remove the subject effect, we applied the data in Table I to a two-way analysis of variance test. As a result, we can see that the classification performance is significantly different when using each projection method. The "PCA" is inferior to the "PCA+SOFM" by an average of 1.265% ($p = 0.000427$) because the PCA transforms the wavelet packet features into a new feature space with the maximum variance of all features. This means that the PCA-reduced features have low class separability. On the other hand, the "SOFM" is superior to the "PCA+SOFM" by an average of 0.761% ($p = 0.004208$) 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 Table II, 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 increment, 125 ms. Accordingly, the SOFM method is inadequate for real-time processing. These evaluation results show that the proposed method is suitable for myoelectric hand control because it can achieve real-time pattern recognition with high accuracy.

B. Analysis of Class Separability by Projection Methods

In this subsection, we analyze the relationship between class separability and recognition accuracy. In Section IV-A, the

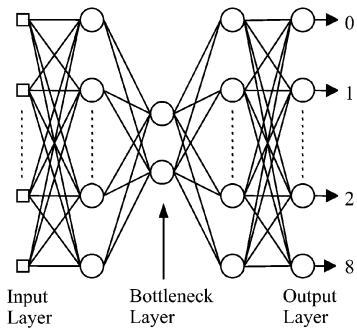

Fig. 5. Structure of MLP with bottleneck layer having two neurons.

PCA-reduced features resulted in lower recognition accuracy caused by unstable MLP outputs. On the other hand, the proposed linear-nonlinear projection method showed stable MLP outputs and high recognition accuracy. This means that the recognition accuracy depends more on the feature class separability than on the MLP performance. The MLP has abilities of both an NLDA and a nonlinear classifier [11]. We compared distributions of the PCA-reduced features and the proposed linear-nonlinear projected features in the NLDA space. To visualize feature distribution and decision surface, we inserted a *bottleneck layer* with two neurons into the proposed MLP classifier, as shown in Fig. 5. In this five-layer MLP, the NLDA network from the input layer to the bottleneck layer maximizes $\mathrm{Tr}(\mathbf{S}_B\mathbf{S}_T^+)$, where $\mathbf{S}_T^+$ and $\mathbf{S}_B$ are the pseudo-inverse of the total scatter matrix and the between-class scatter matrix in the bottleneck layer. The nonlinear classifier from the bottleneck layer to the output layer then constructs a decision surface. Accordingly, in the bottleneck layer, we can see how the input features affect the class separability and classification accuracy of the MLP.

The bottleneck layer corresponding to the NLDA output is shown in Fig. 6. Although MLP has the ability of NLDA for nonlinear mapping, the linear-nonlinear projected features show high class separability and a decision surface with a large separation margin compared to the PCA-reduced features (see Fig. 6). The class separability can be quantitatively expressed by Fisher's index [15]. The Fisher's index is the ratio between the separation of each class and the scattering within a signle class. Thus, the larger Fisher's index signifies a higher class separability of the projected features. Table III shows the Fisher's indexes of the PCA-reduced features, the proposed linear-nonlinear projected features, and their NLDA outputs. From these results, we can see that the recognition accuracy highly depends on the feature class separability. Consequently, the proposed linear-nonlinear projection method improves the class separability and the recognition accuracy.

C. Real-Time Virtual Hand Control Using EMG

Using the proposed EMG pattern recognition method, we implemented a real-time control system for a three-dimensional (3-D) virtual hand, graphically designed using OpenGL. In this experiment, the control system was executed on a 1.8-GHz Pentium IV PC. As an example, we explain the recognition procedure of wrist extension. When the subject made a wrist extension, stronger EMG signals were measured in channels 1 and 4 than in channels 2 and 3. Fig. 7 shows EMG signals in the transient-state from relaxation to wrist extension. The recognized results are shown in the lower part of Fig. 7. The square and circle denote the outputs of the MLP assigned to the relaxation and the wrist extension, respectively. These outputs were generated every 125 ms. This interval is the same as the increment of the data window. First, the subject's intention to make wrist extension was given at time t_1. The wrist extension, however, could not be recognized at time t_a because the pattern recognition was performed using the data sampled at the previous step not including time t_1. After 125 ms, the data window

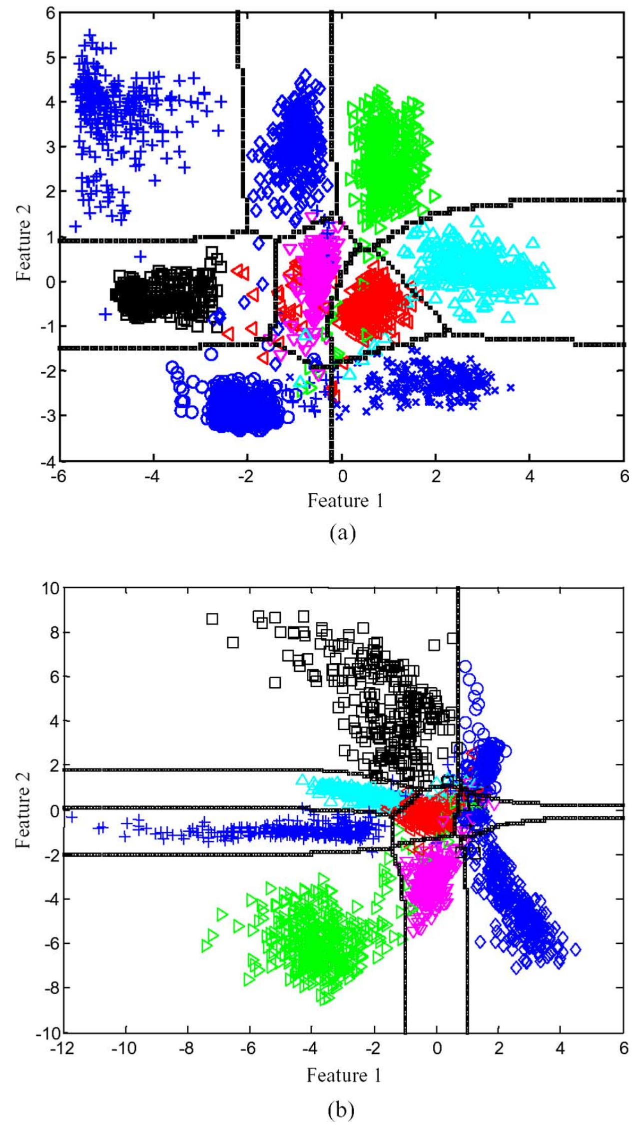

Fig. 6. Feature distribution and decision surface in the bottleneck layer: (a) the linear-nonlinear projected features; (b) the PCA-reduced features.

TABLE III
COMPARISON OF FISHER'S INDEXES

Features	Fisher's index
PCA-reduced features	1.5554×10^{-212}
Linear-nonlinear projected features	3.9277×10^{-5}
PCA-reduced features in bottleneck layer	30.0973
Linear-nonlinear projected features in bottleneck layer	169.8097

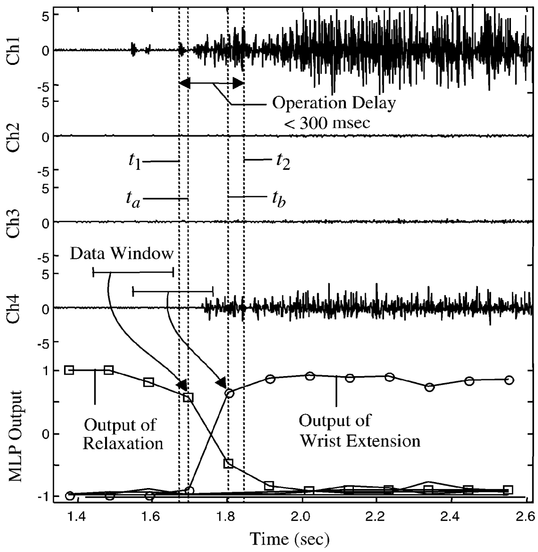

Fig. 7. Transient-state from relaxation to wrist extension.

TABLE IV
PROCESSING TIME IN REAL-TIME PATTERN RECOGNITION

Processes	Processing time (msec)
WPT	30
PCA + SOFM	5
MLP	5
Virtual hand control	40
Others	20
Total	100

was increased, and the wrist extension was recognized at time t_b correctly. Finally, the virtual hand was controlled. Since we implemented the virtual hand using OpenGL, the 3-D graphics needed about 40 ms processing time. Therefore, the virtual hand control was completed at time t_2. Table IV shows that the total processing time was less than the window increment, 125 ms. This result shows that the operation delay is less than 300 ms, and the proposed method is applicable to the control of a multifunction myoelectric hand in real time.

V. CONCLUSION

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 extract a feature vector, the EMG signal was decomposed by wavelet packet transform. The dimension of the wavelet packet features was then reduced by PCA. Subsequently, SOFM nonlinearly transformed the PCA-reduced feature into a new feature space with improved class separability. As a result, the MLP could find a hyperplane with an enhanced separation margin. From analysis of class separability by projection methods, we showed that the recognition accuracy highly depends on the feature class separability, in a manner that complements the capabilities of the MLP. Consequently, the proposed linear-nonlinear projection method improved the class separability and the recognition accuracy. Using the proposed method, nine kinds of motion were recognized from four EMG channels, and the virtual hand was controlled in real time. From the experimental results, we showed that all processes, including hand control, were completed within 125 ms, 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 four degrees of freedom.

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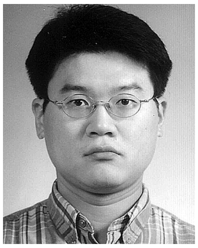

Jun-Uk Chu (M'05) received the B.S. degree in electrical engineering from Yeungnam University, Gyeongsan, Korea, in 1998. He received the M.S. degree in electronics engineering from Kyoungpook National University, Daegu, Korea, in 2000.

Since 2002, he has been a Research Scientist with the Korea Orthopedics and Rehabilitation Engineering Center, Incheon, Korea. His research interests include biosignal processing, pattern recognition, machine learning, and intelligent control.

Inhyuk Moon (M'99) received the B.E. and M.E. degrees in electronics engineering from Gyeongsang National University, Gyeongsang, Korea, in 1992 and 1994, respectively, and the Ph.D. degree in computer-controlled mechanical systems from Osaka University, Osaka, Japan, in 1998.

In 1999, he was a Postdoctral Researcher with the Organization of Hamamatsu Technopolis, Shizuoka, Japan. From 2000 to 2002, he was a Research Professor with the Department of Biomedical Engineering, Yonsei University, Wonju, Korea. From 2002 to 2005, he worked at the Korea Orthopedics and Rehabilitation Engineering Center (KOREC), Incheon, Korea. In 2005, he joined the Department of Mechatronics Engineering, Dong-Eui University, Busan, Korea, where is currently an Assistant Professor. His research interests include pattern recognition, rehabilitation robotics, and biomechatronic engineering.

Mu-Seong Mun received the B.S. and M.S. degrees in mechanical system design from Seoul National University, Seoul, Korea, in 1978 and 1982, respectively. He received the Ph.D. degree in biomedical engineering from the University of Minnesota, Minneapolis, in 1992.

From 1993 to 1994, he worked as a Research Professor with Department of Orthopedic Surgery, Kyunghee University. Since 1994, he has been the Director of the Korea Orthopedics and Rehabilitation Engineering Center, Incheon, Korea. His research interest includes rehabilitation system, assistive products, and orthopedic implants.