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A Supervised Feature Projection for Real-Time Multifunction Myoelectric Hand Control

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***Abstract*—EMG pattern recognition is essential for the control of a multifunction myoelectric hand. The main goal of this study is to develop an efficient feature projection method for EMG pattern recognition. To this end, we propose a linear supervised feature projection that utilizes linear discriminant analysis (LDA). We first perform wavelet packet transform (WPT) to extract the feature vector from four channel EMG signals. For dimensionality reduction and clustering of the WPT features, the LDA incorporates class information into the learning procedure and finds a linear matrix to maximize the class separability for the projected features. Finally, the multilayer perceptron (MLP) classifies the LDA-reduced features into nine hand motions. To evaluate the performance of LDA for the WPT features, we compare LDA with three other feature projection methods. From a visualization and quantitative comparison, we show that LDA has better performance for the class separability, and the LDA-projected features improve the classification accuracy with a short processing time. We implemented a real-time control system for a multifunction myoelectric hand. In experiment, we show that the proposed method achieves 97.2 % recognition accuracy, and that all processes, including the myoelectric hand control, are completed within 97 msec.**

I. Introduction

RECENTLY, several multifunction myoelectric hands have been developed [1]-[2]. These hands have a number of degrees of freedom and dexterous hand functions. Such a multifunction myoelectric hand requires a robust and computationally efficient EMG pattern recognition method to classify and control hand functions. In order to achieve high recognition accuracy in multifunction myoelectric hand control, a number of EMG pattern recognition methods have been proposed [3]-[9]. These works have investigated a variety of feature extraction methods to define the feature vector from the EMG signal. As the number of motions to be classified has increased, researchers have used the multi-channel EMG signals and a combination of various feature vectors to increase the information extracted from EMG signals. That is, feature vectors are expressed with a high dimensionality. For these feature vectors, classification performances have been investigated using various classifiers. However, these studies did not explain why the proposed method enhanced the classification performance, but merely showed the comparison results with other methods. Consequently, there is lack of consideration for the dimension and distribution of feature vectors extracted from EMG signals. To analyze the results of feature extraction, we need a feature projection method in the EMG pattern recognition system. Generally, feature projection can be formulated as a mapping from an original feature space to an appropriate subspace such that a learning criterion is optimized. Feature projection enables us to visualize high dimensional feature vectors in a low dimension and analyze the distribution of the reduced feature vectors. As a result, we can select a classifier that has the best performance for the reduced feature vectors.

The goal of this study is to develop an efficient feature projection method for EMG pattern recognition. The feature projection method is required to reduce the dimensionality of features and cluster features with an improvement of class separability. To this end, we propose a linear supervised feature projection that utilizes LDA. LDA incorporates class information into the learning procedure and finds a linear matrix to maximize the class separability for the projected features. As a result, a classifier can find a decision surface with an enhanced separation margin, and the classification accuracy is improved. Also, the linear projection of LDA allows a short processing time and makes a real-time implementation possible. In this work, using LDA feature projection, we propose the structure of WPT-LDA-MLP for EMG pattern recognition. To recognize nine kinds of hand motion, we first extract wavelet packet features from four channel EMG signals. Then, the LDA performs the dimensionality reduction and the clustering of the WPT features to improve the class separability. In the classification stage, the MLP discriminates the LDA-projected features for different classes. To evaluate the performance of LDA for the WPT features, we compare LDA with principle components analysis (PCA), nonlinear discriminant analysis (NLDA), and self-organizing feature map (SOFM). For these feature projection methods, we perform the visualization of reduced features to show the clustering tendency and investigate the class separability using Sammon's stress and Fisher's index. The results of the classification success rate and processing time show that LDA achieves the best performance. Finally, we implement a real-time EMG pattern recognition system for a multifunction myoelectric hand, and show that the proposed method is suitable for the purpose of controlling the multifunction myoelectric hand in real time.

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II. 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. 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.

In experiment, we used an active surface electrode (DE-2.1, DELSYS), and the EMG signals were digitized by an ADC board (6052E, NI). The sampling frequency was 1024 Hz. EMG data were collected from five normally subjects (three males and two females, 28±2.3 yrs.). Each subject performed nine hand motions including relaxation and conducted twenty sessions. The first ten sessions were used for learning procedures, and the remaining ten sessions were used for evaluation of the recognition performance. In each session, each motion was performed once for a duration of about 4 seconds, and switched between relaxation and static contraction.

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 [5]. We apply a moving window scheme with a window increment to recognize a steady-state motion. For real-time implementation, all processes, including hand control, must be completed within the window increment. In this study, we set the length of the moving window to 250 msec with 125 msec window increment. This guarantees that the user can control a directed myoelectric hand function within 300 msec from the instant when the user's intention is given.

III. Algorithm Description

To extract a feature vector from EMG signals, we use a WPT. We first calculate the time-frequency energy maps of classes in each subspace and use the energy maps as the inputs to the symmetric relative entropy. To determine the best basis, we use the local discriminant basis (LDB) algorithm. In the LDB algorithm, discrete wavelet decomposition was implemented using the Mallat algorithm. We specified the depth of the decomposition level as four, and used the Haar wavelet and scaling function. To increase the class separability, we independently constructed 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. The feature set for each channel is a 256-dimensional feature vector, and the feature set for four channels is a 1024-dimensional feature vector.

In this study, EMG pattern recognition is a supervised classification problem in which the training pattern is identified as a member of a predefined class. Therefore, we search the LDB of the WPT in a supervised manner using the class information of the segmented EMG signals. And then, we apply the WPT features to a supervised feature projection method because it can use the class information for the learning criterion such that feature vectors belonging to the same class are clustered. We adopt LDA as a linear supervised feature projection method. The LDA [10] finds a linear matrix to make the between-class scatter large and the within-class scatter small. That is, the LDA seeks a coordinate system to maximize the class separability for the projected features. To determine the dimensionality of the projected feature, we examined the linear dimensionality for the 1024-dimensional WPT features extracted from EMG signals. As a result, the linear dimensionality of the WPT features is eight. This means that the ratio of the sum of the eight largest eigenvalues to the sum of the total eigenvalues of the covariance matrix is more than 0.97. Therefore, we projected the WPT features into an eight-dimensional subspace through the LDA.

After feature projection, the reduced features are given to the MLP classifier. The input layer of the MLP is constructed from the eight outputs of the LDA. The number of hidden layers is two, and each hidden layer has nine neurons. The output layer has nine neurons for the nine kinds of hand motion to be recognized. When the LDA-projected features were applied to the MLP, we selected the maximum output of the MLP as the recognized motion.

IV. Performance Evaluation

For feature projection methods, the mapping function can be either linear or nonlinear and the learning procedure can be either a supervised or unsupervised method. In this section, to evaluate the proposed EMG pattern recognition method, we investigate the performance of four methods, including our method. Each method uses LDA (linear supervised), PCA (linear unsupervised), NLDA (nonlinear supervised), and SOFM (nonlinear unsupervised) for feature projection, respectively.

We first visualize the projection results of the test dataset for one subject. Fig. 1 shows the reduced features by using (a) LDA, (b) PCA, (c) NLDA, and (d) SOFM. For LDA and NLDA, the features for different classes are well separated because these methods utilize supervised learning criteria. On the other hand, the clusters of features in the PCA plot are overlapped. This is due to the fact that PCA performs orthogonal projection to retain the variance of all features. Although SOFM clustered the features belonging to the same class well, some features were mis-clustered with a large distance from the desired cluster. The reason is that SOFM nonlinearly transformed the WPT features without the class information.

Sammon's stress [11] is a measure of how much the interpattern distances are changed when the patterns are projected from the original feature space to the reduced feature space. Fisher's index [12] is a measure of the class separability of the projected features. We performed the projections on the test dataset for five subjects. Table I lists the average Sammon's stress and Fisher's index values for

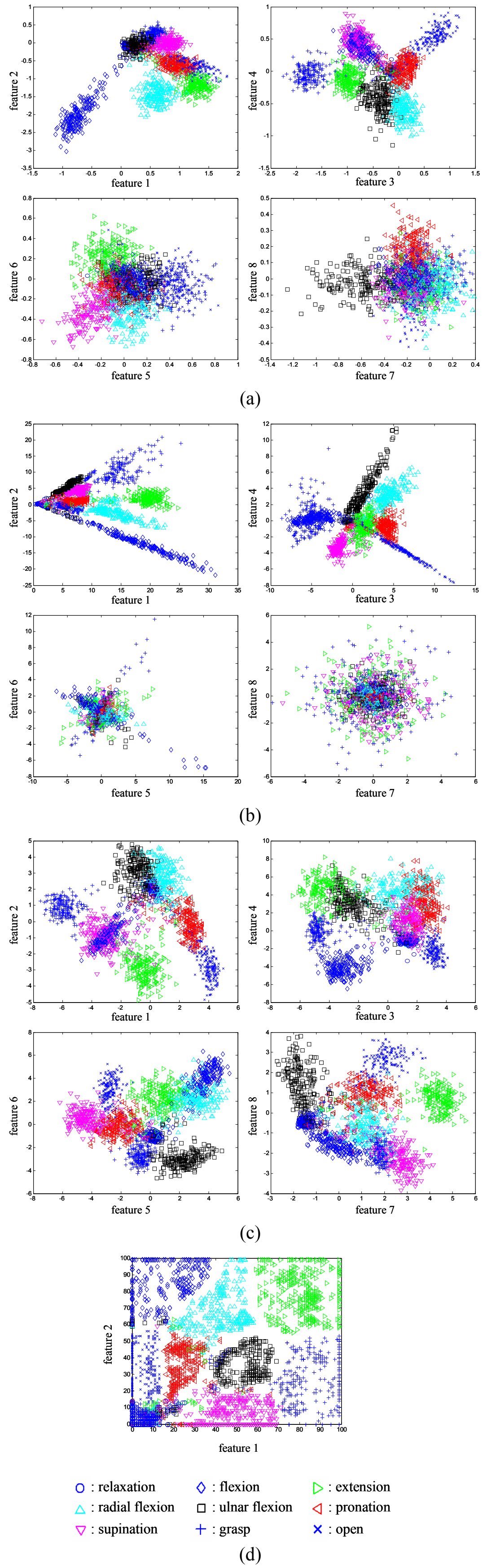

Fig. 1. Dimensionally-reduced feature spaces using (a) LDA, (b) PCA, (c) NLDA, and (d) SOFM.

TABLE I
THE AVERAGE VALUES OF SAMMON'S STRESS AND FISHER'S INDEX.

	LDA	PCA	NLDA	SOFM
Sammon's stress, E	0.8402	0.2503	0.8475	0.8875
Fisher's index, J	17928.4	0.0032	2997.6	28.0875

TABLE II
THE AVERAGE VALUES OF THE MLP CLASSIFICATION SUCCESS RATE AND PROCESSING TIME.

	LDA	PCA	NLDA	SOFM
success rate [%]	97.2	94.9	97.3	95.6
processing time [msec]	2	2	150	300

the four projection methods. Although the LDA is a linear projection, it generated a large Sammom's stress value similar to those of NLDA and SOFM. This happens because LDA projected the features onto the non-orthogonal principal vectors to maximize the class separability. In Fisher's index, LDA naturally has the best performance. We can see that the supervised methods are superior to the unsupervised methods for class separability.

We applied the projected features to the MLP classifier. We performed the classifications on the test dataset for five subjects. At the same time, we tested the processing time for the four projection methods. These experiments were executed on a 1.8 GHz Pentium IV PC. Table II shows the average values of the MLP classification success rate and processing time for the four projection methods. We can see that NLDA and LDA have higher success rates than those of PCA and SOFM. This result is consistent with the comparative results of the class separability. However, NLDA and SOFM needed much more processing time owing to the nonlinear computations for the high dimensional features. To implement real-time pattern recognition, the processing time should be less than the window increment, 125 msec. Accordingly, NLDA and SOFM are inadequate for real-time processing. These results show that LDA has better performance for the class separability, and the LDA-projected features improve the classification accuracy. In addition, the short processing time of LDA is suitable for a real-time EMG pattern recognition.

V. REAL-TIME MULTIFUNCTION MYOELECTRIC HAND CONTROL

Using the proposed EMG pattern recognition method, we implemented a real-time control for a multifunction myoelectric hand developed in this study. The experimental setup consists of four surface electrodes, an amplifier and filter system, a PC with ADC and timer board, a graphic user interface, and a multifunction myoelectric hand. The developed hand has four DOFs, including pronation and supination, radial flexion and ulnar flexion, wrist flexion and extension, and hand open and grasp. The total length and weight of the hand are 200 mm and 790 g, respectively. Each joint is actuated by a RC-servo motor (HSR-5995TG, HITEC), which embedded a position controller with potentiometer feedback. The control commands are given by

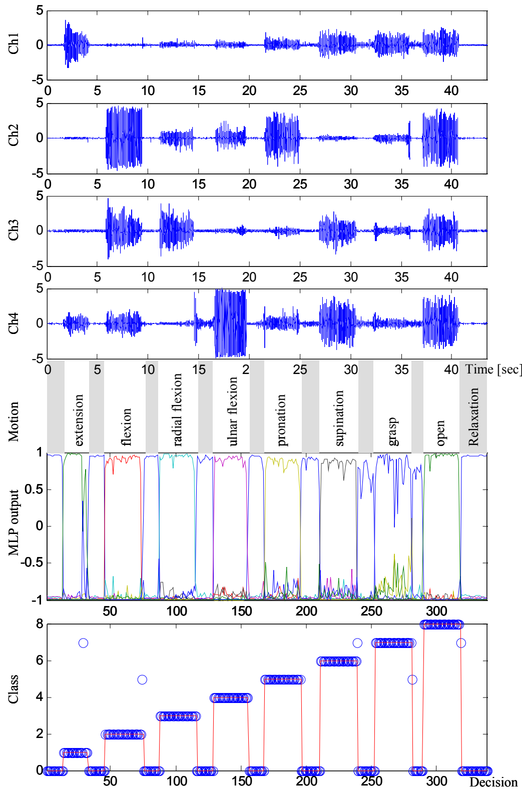

Fig. 2. Four channel EMG signals and recognized results.

TABLE III
THE AVERAGE VALUES OF PROCESSING TIME IN REAL-TIME PATTERN RECOGNITION.

Processes	Processing time [msec]
Wavelet packer transform	30
Linear discriminant Analysis	2
Multilayer perceptron	5
Myoelectric hand control	40
Others	20
Total processes	97

a 20 msec cycle pulse train with variable duty rates. We used a timer board (6601, NI) to generate the pulse train.

Fig. 2 shows the four channel EMG signals and the recognized results by the proposed method in real time. The EMG signals are typical data recorded from a typical subject. The subject performed nine hand motions, and each motion was switched between relaxation and static contraction. The middle of Fig. 2 shows the MLP output values within -1.0 to 1.0. The maximum output is selected as the recognized motion in every decision. The recognized results are shown in the bottom of Fig. 2, where each motion is assigned to the numbers 0 to 8. The solid line and open circle denote the desired output and recognized motion, respectively. The results are stable in steady-state motions with the exception of transient-state motions. In this real-time experiment, the proposed method achieved correct classification accuracy as high as 97.2%. This result is consistent with that of the off-line experiment in the previous section. Table III shows that the total processing time was 97 msec less than the window increment, 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.

VI. CONCLUSION

This paper proposed a real-time EMG pattern recognition system for a multifunction myoelectric hand control. The system was composed of WPT, LDA, and MLP. To recognize the nine kinds of hand motion from the four channel EMG signals, we first extracted the features by WPT. Subsequently, we used LDA as a linear supervised feature projection to reduce the dimensionality of the WPT features and improve the class separability. Finally, we applied LDA-projected features to the MLP. From the visualization and quantitative comparison, the LDA projection has better performance for the class separability, and the LDA-projected features make the classification accuracy improve with a short processing time. Using the proposed method, we implemented a real-time EMG pattern recognition system for a multifunction myoelectric hand developed in this study. From the experimental results, we showed that the proposed method achieved high recognition accuracy, and the subject could control the myoelectric hand without a preserved operation time delay.

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