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A Comparative Study on PCA and LDA Based EMG Pattern Recognition for Anthropomorphic Robotic Hand*

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Abstract— **A multifunctional myoelectric prosthetic hand is a perfect gift for an upper-limb amputee, however, the myoelectric control for a prosthetic hand is not so good now. Here, the paper presents a comparative study on electromyography (EMG) pattern recognition based on PCA and LDA for an anthropomorphic robotic hand. Four channels of surface EMG (sEMG) signals were recorded from the subject's forearm. Time-domain analysis, frequency-domain analysis, wavelet transform analysis, nonlinear entropy analysis and fractal analysis were done and fourteen kinds of features were extracted from sEMG signals. The features were divided into four groups, and the performances of the four groups were compared and analyzed. In the feature projection stage, three schemes were proposed and their performances were compared with each other. The first one only used the principal component analysis (PCA) for dimension reduction. And the second one only used the linear discriminant analysis (LDA) for dimension reduction. The third one used PCA for the first step of dimensionality reduction, and then used LDA for the next step of dimensionality reduction. In the classification stage, minimum distance classifier (MDC) was employed for identifying nine kinds of hand/wrist motions in the projected space. Comparative experiments of four groups of features and three projection schemes were done and evaluated. The online experiment of real-time myoelectric control for an anthropomorphic robotic hand was done as well.**

I. INTRODUCTION

Nowadays, many disabled people who have lost limbs in wars, car accidents, and industrial accidents are provided with prosthetic devices to face challenges in their daily life. Advanced commercial prosthetic hand such as Otto Bock hand [1], i-Limb hand [2], and Smart hand [3] have been able to achieve some motions like human hands. And these devices could help amputee persons improve the quality of life at physical and psychological aspects. The approach using electromyography (EMG) signals from amputee persons' remnant muscles to control prosthetic devices is beneficial to restore the missing functionality of amputated limbs, and it has a history of about 40 years [4]-[6]. Previous commercial EMG-based prosthetic devices primarily adopt a conventional threshold or proportional control strategy to achieve a few simple actions such as hand opening and closing [7]. In recent years, myoelectric pattern recognition for a prosthesis system has attracted increasing attention [8].

In an EMG pattern recognition system, feature extraction is the process that converts original sEMG signals to a compact and informative set of features [9]. So far, many feature analyzing methods have been applied to EMG pattern recognition problems. L. Hargrove et al. [10] indicated that the combination of the time-domain features and the autoregressive (AR) features had outstanding performance in EMG pattern recognition. In [11], discrete wavelet transform was compared with the combination of integral of sEMG (IEMG) and power spectral density (PSD) for six simple hand motions. In the previous work [12], we extracted five time-domain features including the mean absolute value (MAV), root mean square (RMS), zero crossings (ZC), Waveform length (WL) and slope sign changes (SSC) and four frequency-domain features including the power spectral density (PSD), median frequency (FMN), median frequency (FMD) and auto-regressive coefficients (AR).

Traditional methods such as time-domain and frequency-domain analyzing methods have been widely utilized in EMG pattern recognition, and they have a good capability to track muscular changes. However, these methods are not effective in detecting the critical feature of sEMG signals during transient human movements. A sEMG signal which is a complex signal embedded in noise is non-stationary and stems from a high-dimensional nonlinear system. Therefore, nonlinear methods such as nonlinear entropy analysis and fractal analysis recently have been proposed to analyze sEMG signals for extracting some informative features which can detect the changes in different muscle statuses. Zhao Jingdong et al. [13] extracted sample entropy and wavelet transform coefficients from three channels of sEMG signals for classifying six fingers movements. The fractal dimension features were utilized for identifying finger movements in [14]. Actually, nonlinear features can only be seen in a few literatures owing to their high complexity. Researchers commonly just focus on one or two kinds of nonlinear features and illustrate the experimental results in EMG pattern recognition. This study will do nonlinear entropy analysis and fractal analysis and extract four representative features. The traditional methods including time-domain analysis, frequency-domain analysis and wavelet transform analysis will be utilized as well, and ten frequently-used features will be extracted. The total fourteen features from five analyzing methods will be divided into four groups, and the recognition performances of the four groups of features will be studied comparatively.

In order to recognize more motion patterns, more channels of sEMG signals and more kinds of features are used to increase the information extracted from sEMG signals. This

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leads to a high dimensionality of the feature vector. Thus, feature projection is needed in EMG pattern recognition. Feature projection could map high dimensional original features to an appropriate low dimensional space. And feature projection could be optimized by a learning criterion so that the features belonging to the same class are clustered and the generalization ability is improved. In addition, dimensionality reduction of feature projection reduces the processing time of pattern recognition, and is beneficial to meet the demand of the real-time control. The principal component analysis (PCA) is a conventional method which can project high dimension data into a low dimension space and make the data not relevant in the low dimension space. The paper [13] adopted PCA to reduce the dimensionality of WPT coefficients from four channel EMG signals. In this study, PCA is used to carry out the first step of dimensionality reduction considering that PCA merely generates a well-described coordinate space of the features without considering class separation. The linear discriminant analysis (LDA) could reduce the dimensionality of features and meanwhile take the class separability into account. Plus, LDA just needs a short processing time. Therefore, in the study, LDA is used for the second step of dimensionality reduction considering that the combination of PCA and LDA projection may obtain a better integrated merits deriving from both the two methods. In the classification stage, the minimum distance classifier (MDC) is employed to recognize the projected features.

In the previous work [12], we have used five time-domain features and four frequency-domain features from four channels of sEMG, and have compared the performance of LDA and PCA+LDA for classifying five kinds of hand motions. The goal of this study is to find an efficient feature projection method based on PCA and LDA for EMG pattern recognition and to compare and evaluate the performance of four groups of features derived from the five analyzing methods including time-domain analysis, frequency-domain analysis, wavelet transform analysis, nonlinear entropy analysis and fractal analysis, and finally to construct a most efficient EMG pattern recognition system for nine kinds of hand/wrist motions. In this study, the pattern recognition system consists of the feature extraction including five kinds of analysis methods, PCA feature projection, LDA feature projection and MDC classification, as shown in Fig. 1. The PCA+LDA projection is compared with PCA projection and LDA projection respectively. Finally, the real-time EMG pattern recognition system is implemented for an anthropomorphic robotic hand, and its performance is demonstrated.

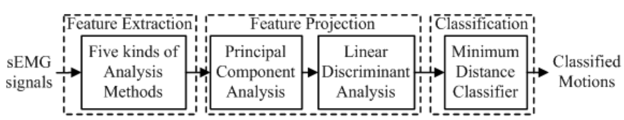


Figure 1. Block diagram of EMG pattern recognition system.

II. Data Acquisition

This study attempted to recognize nine kinds of hand/wrist motions: hand closing (HC), hand opening (HO), index finger pinching (IFP), middle finger pinching (MFP), wrist flexion (WF), wrist extension (WE), wrist radial deviation (WRD), wrist ulnar deviation (WUD) and relaxing motion (RM) as shown in Fig. 2. Four surface electrodes were used to acquire the sEMG signals from the extensor digitorum, flexor digitorum superficialus, extensor carpiradialis, and flexor carpiulnaris, respectively, which are concerned with the nine motions. In order to collect high quality sEMG signals, the skin was scrubbed with alcohol and shaved if necessary, and then the electrodes with conductive gel were attached to the corresponding positions as shown in Fig. 3.

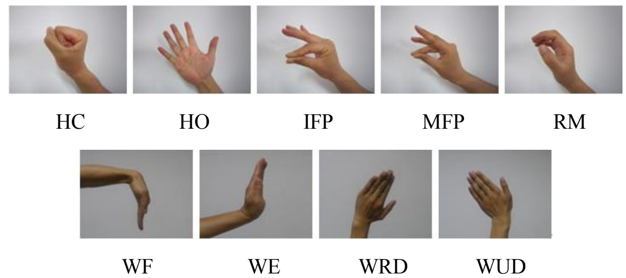


Figure 2. Nine kinds of hand/wrist motions.

Figure 3. The placement of surface electrodes on a left forearm.

Since the amplitude of sEMG signals is at range of 100~5000uV, and the spectrum is mainly distributed in 10~500Hz, the study adopts the MyoScan EMG Sensor (see Fig. 4), whose parameters are shown in Table I. The sEMG signals are digitized by an A/D converter card, Advantech PCI-1716, and each channel is sampled at a rate of 1000 Hz with 16-bit resolution.

Figure 4. MyoScan EMG Sensor

TABLE I. The Senor's Parameters

Sensor's Parameters	parameters				
	Power supply	***Amplifying rate***	***Input signal range***	***Active frequency range***	***Sampling rate***
values	7.2V	500	0-2000uV	10-500Hz	2048s/s

In this study, sixteen groups of sEMG signals were collected from one intact-limb subject's forearm. The first eight groups were used for the training section, while the remaining eight groups were used for the test section. For each group, the time of data acquisition was 32 seconds, 2 seconds for each active motion (the nine motions except the relaxing motion), and a 2-second relaxing motion between each two active motions. There was a two minutes rest time between every two groups to prevent muscle fatigue.

III. Feature Extraction

In order to control an robotic hand in real time without perceiving a time delay, the processing time of EMG pattern recognition should be less than 300 msec. Thus, the scheme of a sliding window with an incremental window was adopted for the steady-state motion recognition. For the real-time myoelectric hand control, all the processes including transmitting control commands should be completed within an incremental window. In this study, a 128-msec (128 samples) sliding window with a 32-msec (32 samples) incremental window was selected. After data segmentation, fourteen features would be extracted in a sliding window. In this study, we would use the five analyzing methods including the time-domain analysis, frequency-domain analysis, wavelet transform analysis, nonlinear entropy analysis, and fractal analysis.

Time-domain analysis is one of the simplest and most common feature analyzing methods. We selected six typical EMG features including the mean absolute value (MAV), root mean square (RMS), zero crossings (ZC), waveform length (WL), slope sign changes (SSC), and autoregressive model coefficients (ARC). Here, the 4-order autoregressive model was adopted, and the parameters a1, a2, a3, a4 were chosen as EMG features.

Frequency-domain analysis is another traditional analyzing method for EMG recognition. Average power (AP), mean frequency (FMN), and median frequency (FMD) were used to extract the frequency spectrum information from the sEMG signals in the study.

Wavelet transform analysis is one kind of time-frequency-domain analyzing methods, which can simultaneously obtain time information and frequency information from signals. In this study, 3-layer wavelet decomposition and reconstruction were implemented, and the mean values of coefficients d1, d2, d3, a3 were used as EMG features. Experimental results indicated that the mean value used less processing time yet obtained even higher identification accuracy compared to the singular value deriving from singular value decomposition in the study.

Nonlinear entropy analysis is a promising approach to characterize non-stationary and nonlinear EMG signals. In this study, the nonextensive entropy (TE) and sample entropy (SE) were chosen to extract nonlinear information from sEMG signals.

Fractal analysis is a new approach to describe the inherent self-similarity and long-range correlation of sEMG signals. Correlation dimension (D_C) and box dimension (D_B) are two representative parameters of fractal dimension, thus they were selected as EMG features for motion recognition in this study.

In total, 14 kinds of features deriving from five analyzing methods were extracted from 4 channels of sEMG signals. Some of those features are shown as Fig. 5. These features were divided into 4 groups according to their performance and category (see Table II). Group A includes 6 kinds of time-domain features. Group B contains 3 kinds of frequency-domain features and wavelet transform coefficients (WTC). Group C consists of 2 kinds of nonlinear entropy features and 2 kinds of fractal dimension features. Group D is the combination of 3 kinds of time-domain features and wavelet transform coefficients (WTC).

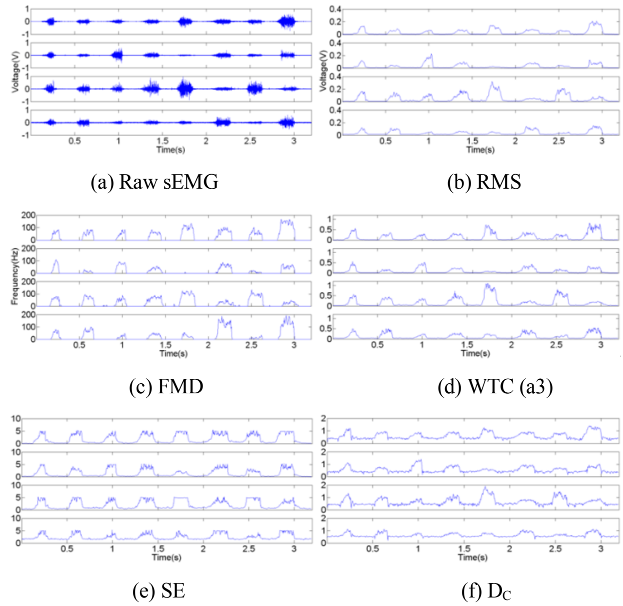


Figure 5. Some features extracted from 4 channels of sEMG signals

TABLE II. THE FEATURE GROUPING

Feature Grouping	Groups			
	Group A	*Group B*	*Group C*	*Group D*
features	MAV, RMS, ZC, WL, SSC, ARC	AP, FMN, FMD, WTC	TE, SE, D_C, D_B	RMS, WL, SSC, WTC

IV. FEATURE PROJECTION AND CLASSIFICATION

With the increase of the number of channels and features, the feature vector becomes a high-dimensional vector. In order to realize EMG pattern recognition efficiently, feature projection is necessary to map a high-dimension feature vector to an appropriate lower dimension space. Feature projection could make the feature vectors which belong to the same class clustered, and improve the generalization ability of the classifier. In addition, dimensionality reduction of feature projection could reduce the computational cost of EMG pattern recognition. In order to find the best feature projection scheme, the three projection schemes were compared in this study (see Fig. 6). The first one was just using PCA for the feature projection. The second one was that the principal component analysis (PCA) was used for the first step of feature projection, and then the linear discriminant analysis (LDA) was used for the next step of feature projection. And the third one was just using LDA for the feature projection. In this study, the three projection schemes are written as PCA, PCA+LDA, and LDA for short.

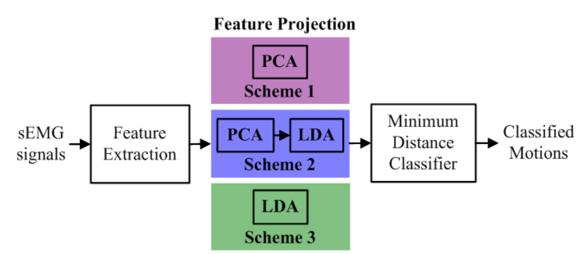


Figure 6. Schematic diagram of the three feature projection schemes

As described in the previous work [12], PCA can project feature vectors from a high-dimension space onto a low-dimension space, and make the variance of data maximum in the low-dimension space. Suppose that $X=(X_1,X_2,\ldots,X_n)^T$ is an n-dimension random variable, $Y=(Y_1,Y_2,\ldots,Y_m)^T$ is an m-dimension random variable, $C=1/(n-1)\sum(X_i-u)(X_i-u)^T$ is the covariance matrix of the samples. Assume that there is a linear transformation:

$$\begin{cases} Y_1 = a_{11}X_1 + a_{21}X_2 + \cdots + a_{n1}X_n = a_1^T X \\ Y_2 = a_{12}X_1 + a_{22}X_2 + \cdots + a_{n2}X_n = a_2^T X \\ \vdots \\ Y_m = a_{1m}X_1 + a_{2m}X_2 + \cdots + a_{nm}X_n = a_m^T X \end{cases} \tag{1}$$

The problem of solving $Var(Y_i)$ maximum value can be transform into solving the following optimization problem:

$$\begin{cases} \max \quad a_1^T C a_1 \\ \text{s.t} \ \ a_1^T a_1 = 1 \end{cases} \tag{2}$$

To solve the problem the Lagrange multiplier is used, and the formula $Ca_i = \lambda a_i$ is gotten. And then the principal components could be gotten. In general, The i-th principal component of X can be obtained by solving the corresponding eigenvector of the i-th largest eigenvalue, and they are usually required to be independent of each other in order to make the information they contains not overlapping.

Finally, a set of orthogonal basis $(a_1, a_2,\ldots, a_m)$, denoted by A, is obtained, and it can project n-dimension random variables $X=(X_1,X_2,\ldots,X_n)^T$ for $m(m<n)$-dimension random variables $Y=(Y_1,Y_2,\ldots,Y_m)^T$ by (3), achieving dimensionality reduction meanwhile retaining the maximum information.

$$Y = A^T X \tag{3}$$

As described in the previous work [12], LDA projects high-dimension vectors onto an optimal discriminant space to extract class information and reduce the vector dimension, and makes sure that the projected vectors have the largest between-class distance and the smallest within-class distance. The between-class scatter matrix and the within-class scatter matrix are defined as follows:

$$S_b = \sum_{i=1}^{c} n_i (u_i - u)(u_i - u)^T \tag{4}$$

$$S_w = \sum_{i=1}^{c} \sum_{x_k \in class\ i} (u_i - x_k)(u_i - x_k)^T \tag{5}$$

Where $u_i=1/n\sum x$, ($x \in$ class i) is the mean of the i-th sample, $u=1/m\sum x_i$ is the mean of the total samples, m is the number of the total samples, n_i is the number of the sample i, c is the number of the classes, and $n_1+n_2+\ldots+n_c=m$. LDA needs the lower between-class coupling degree and higher within-class polymerization degree. Thus, the Fisher criterion is introduced:

$$J(W) = \frac{\left\| W^T S_B W \right\|}{\left\| W^T S_W W \right\|} \tag{6}$$

The optimal projection matrix W can be gotten by maximizing J(W). It is easy to prove, to maximize J(W), $S_B W = \lambda S_W W$ must be met. A sample X can be projected onto the LDA optimal discriminant space to get a new sample Y, as the following equation

$$Y = W^T X \tag{7}$$

For the PCA+LDA projection scheme, the matrices A and W can be obtained sequentially in the training stage, and then a sample X can be projected onto the PCA+LDA combination projected space to obtain a new sample Y, as the following equation

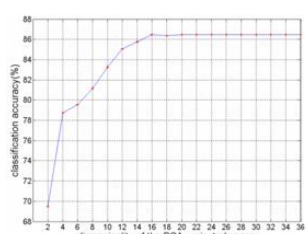
$$Y = A^T W^T X \tag{8}$$

The minimum distance classifier (MDC) is one of the simple and efficient classification methods. MDC firstly calculates the center of each class, and then finds the class which has the minimum distance from the given input sample to the class center, and the input sample is classified into the minimum distance class. In this study, MDC is an appropriate classifier because the projected feature vectors are easy to indentify in a low-dimensional space, thus a complex classifier is not necessary. In addition, MDC needs very short computing time.

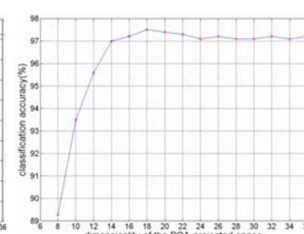
V. Experimental Results and Discussions

A. Comparison of three feature projection schemes

In this section, PCA, LDA, and PCA+LDA were compared with each other. The features of Group A (including MAV, RMS, ZC, WL, SSC, and ARC) were adopted in this comparative study. For the PCA projection scheme, an appropriate dimensionality of the PCA-projected space was obtained by the experiments. As can be seen in Fig. 7(a), when the dimensionality reaches 16, the classification accuracy mostly reaches the maximum. Thus, 16 was selected as the optimal dimensionality of the PCA-projected space. For PCA+LDA projection scheme, as Fig. 7(b) shows, the classification accuracy reaches maximum when the dimensionality is 18. Therefore, 18 was obtained as the parameter for the PCA+LDA scheme.



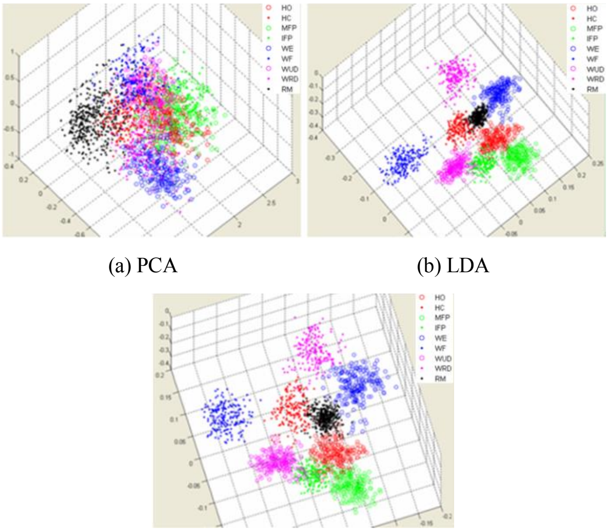
(a) The scheme of PCA



(b) The scheme of PCA+LDA

Figure 7. The classification accuracy vs the dimensionality in the PCA-projected spaces of the PCA and PCA+LDA schemes.

The first eight groups of sEMG signals were used for training the projected matrices of the three feature projection schemes. The signals of nine kinds of hand/wrist motions were segmented from the eight groups respectively. The features of Group A were extracted from the segmented samples, and then they were used for training the feature projected matrices. After training, the feature projected matrices and the centers of nine kinds of hand/wrist motions were obtained, and the clustering effects of the three projection schemes can be observed in the projected space. Fig. 8 shows the clustering effects of nine kinds of hand/wrist motions in the projected spaces of three feature projection schemes respectively.



(a) PCA (b) LDA

(c) PCA+LDA

Figure 8. The clustering effects in the projected spaces of three feature projection schemes respectively.

The last eight groups of sEMG signals were used for test, and the classification result of one group of signals is shown in Fig. 9. In the figure, HC, HO, IFP, MFP, WF, WE, WRD, WUD, RM are labeled as 1, 2, 3, 4, 5, 6, 7, 8, 9, respectively. The burrs in the figure are the wrongly classified sample points. The number of the wrongly classified samples was counted and then was used for calculating the classification accuracy. The classification accuracy and the processing time are shown in Table III. The process of the processing time consists of feature extraction of Group A, feature projection of each scheme, and MDC classification. The experiments were executed on 2.66GHz Intel(R) Core(TM)2 Quad CPU PC.

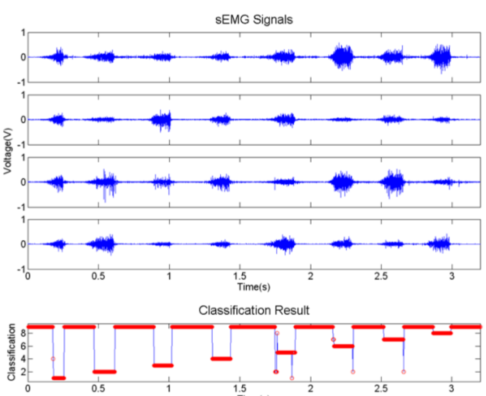


Figure 9. the classification result of one group of sEMG signals

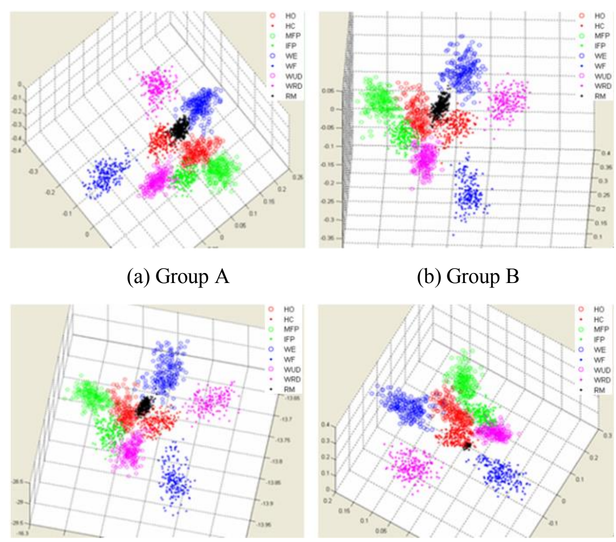
TABLE III. AVERAGE VALUES OF CLASSIFICATION ACCURACY AND PROCESSING TIME OF THREE FEATURE PROJECTION SCHEMES

Classification Performance	**Feature Projection Schemes**		
	PCA	***LDA***	***PCA+LDA***
Classification accuracy [%]	85.6±2.2	97.4±0.8	97.5±0.7
Processing time [msec]	0.478	0.495	0.51

Experimental results showed that PCA had a poor classification performance compared with the other two schemes, and the classification accuracy of LDA and PCA+LDA was very close to each other. PCA is a good tool for dimensionality reduction, yet lacks of the ability of the class separation. LDA considers the class separabillity when it learns from the training samples to obtain a linear optimal projected matrix. Thus, LDA had a higher accuracy than PCA. Though PCA+LDA did not bring complex computation to the projection process, it could not improve the performance of the pattern recognition much. Because the three projection schemes all obtained a projected linear matrix in the end, the processing time of them had no big difference.

B. Comparison of four groups of features

In this section, a comprehensive comparative study on the performance of four groups of features (see Table II) deriving from five analyzing methods was done. The LDA feature projection scheme was adopted for the comparative study. Four groups of features were extracted, and then they were projected to the LDA-projected space, and finally four groups of the projected features were classified by the MDC classifier, respectively. In the study, the first eight groups of sEMG signals were used for training, and the remaining eight groups were used for test. The clustering effects of four groups of features in the LDA-projected space are shown in Fig. 10. The classification accuracy and the processing time of four groups of features are shown in Table IV. The process of the processing time consists of feature extraction of each group, LDA projection, and MDC classification. The experiments were executed on 2.66GHz Intel(R) Core(TM)2 Quad CPU PC.



(a) Group A (b) Group B

(c) Group C (d) Group D

Figure 10. The clustering effects of four groups of features in the LDA-projected space.

TABLE IV. AVERAGE VALUES OF CLASSIFICATION ACCURACY AND PROCESSING TIME OF FOUR GROUPS OF FEATURES

Classification Performance	**Four Groups of features**			
	Group A	***Group B***	***Group C***	***Group D***
Classification accuracy [%]	97.4 ± 0.8	95.1 ± 1.2	94.1 ± 1.5	96.2± 0.9
Processing time [msec]	0.5	37.1	320.1	4.3

It is not easy to see differences between each group from the clustering effects, because the classification accuracy of the four groups had no big difference from each other. And all the features deriving from five analyzing methods had a good class separabillity on EMG pattern recognition. However, the processing time of the four groups had a big difference from each other. The time-domain features from Group A just needed a very short processing time, yet the nonlinear entropy and fractal analysis features from Group C needed a very long processing time. The frequency-domain features from Group B had a bearable processing time for some real-time applications. The wavelet transform features from Group D had a short processing time. The complexity of the features has a dominant part of the processing time. If a feature with complex calculation hasn't an outstanding classification performance, it should not be selected for real-time recognition application. The comparative results indicate that the time-domain features and wavelet transform features are good choices for real-time EMG pattern recognition owning to their excellent performance both in the classification accuracy and processing time, and it is not wise to focus excessively on new complex features for real-time EMG pattern recognition. Nevertheless, long time-consuming features may be good choices for the applications without real-time need, for example some frequency-domain features have a good performance on muscle fatigue study based on EMG.

C. *Real-time myoelectric control for anthropomorphic robotic hand*

In order to verify the performance of the proposed pattern recognition system in real-time applications, the structure consisting of Group A features, PCA+LDA feature projection, and MDC classification was employed. An anthropomorphic robotic hand which can implement the nine kinds of hand/wrist motions was chosen. An accompany video is available at http://ieeexplore.ieee.org, and Fig. 11 is one screen shot of the video. Experimental result showed that the anthropomorphic robotic hand could implement nine kinds of hand/wrist motions well as the subject did without perceiving a time delay for that the control circle was within an increment window (32msec). The subject had an extended physiological proprioception during a long time implementation.

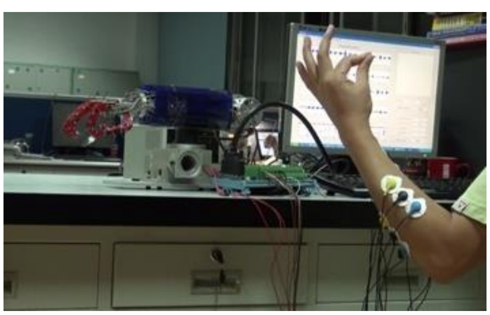


Figure 11. Online real-time control experiments

VI. CONCLUSION

In this paper, we have done a comparative study on an EMG pattern recognition system based on PCA and LDA for an anthropomorphic robotic hand. Four groups of features deriving from five analyzing methods were studied comparatively. The three feature projection schemes including PCA, LDA and PCA+LDA were compared with each other. Nine kinds of hand/wrist motions were selected, and four channels of sEMG signals from human's forearm were collected. Experimental results indicated that PCA+LDA projection didn't improve the recognition performance much compared to LDA projection, and the time-domain features and wavelet transform features were able to obtain a better performance on both the classification accuracy and the processing time compared to the frequency-domain features, nonlinear entropy features and fractal analysis features. In this study, the features of Group A going with PCA+LDA projection and MDC classification obtained the classification accuracy of $97.5 \pm 0.7\%$, and just needed the processing time of 0.51msec. The online real-time myoelectric control for the anthropomorphic robotic hand was implemented, and experiments showed that the anthropomorphic robotic hand was synchronized nicely with the human's hands without perceiving a time delay.

REFERENCES

[1] Otto Bock HealthCare, Product Brochure, Feb.2013, Available: http://www.living-with-michelangelo.com/fileadmin/downloads/techniker/english/technician_product_brochure.pdf

[2] Touch Bionics, Inc., i-Limb Ultra Data Sheet, Feb. 2013, Available: http://www.touchbionics.com/media/2210/i-limb%20ultra%20data%20sheet%20lo-res.pdf

[3] C. Cipriani, M. Controzzi, and M. C. Carrozza, "The SmartHand transradial prosthesis," *NeuroEng. Rehabil. J.*, vol. 8, p. 29, 2011.

[4] R. N. Scott, "Myoelectric control of prostheses," *Arch. Phys. Med. Rehabil. J.*, vol. 47, no. 3, pp. 174–81, Mar. 1966.

[5] P. A. Parker and R. N. Scott, "Myoelectric control of prostheses," *Crit. Rev. Biomed. Eng. J.*, vol. 13, no. 4, pp. 283–310, 1986.

[6] P. Parker, K. Englehart, and B. Hudgins, "Myoelectric signal processing for control of powered limb prostheses," *Electromyogr. Kinesiol. J.*, vol. 16, no. 6, pp. 541–8, Dec. 2006.

[7] L. Dipietro, M. Ferraro, J. J. Palazzolo, H. I. Krebs, B. T. Volpe, and N. Hogan, "Customized interactive robotic treatment for stroke: EMG-triggered therapy," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, no. 3, pp. 325–334, Sep. 2005.

[8] M. B. I. Raez, M. S. Hussain, F. Mohd-Yasin, "Techniques of EMG Signal Analysis: Detection," *Processing, Classification and Applications, Biological Procedures Online (BPO)*, vol. 8, pp. 11–35, 2006.

[9] I. Guyon, S. Gunn, M. Nikravesh, and L. A. Zadeh, "Feature Extraction: Foundations and Applications," *Berlin, Heidelberg: Springer-Verlag*, 2006.

[10] L. Hargrove, K. Englehart, and B. Hudgins, "A comparison o f surface and intramuscular myoelectric signal classification," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 5, pp. 847–853, May 2007.

[11] F. Zhang, P. Li, Z. Hou, Y. Chen, F. Xu, J. Hu, Q. Li, and M. Tan, "SEMG feature extraction methods for pattern recognition of upper limbs," in *Proc. IEEE Int. Conf. Adv. Mechatron. Syst.*, pp. 222–227, Aug. 2011.

[12] D. Zhang, A. Xiong, X. Zhao, and J. Han, "PCA and LDA for EMG-based Control of Bionic Mechanical hand," in *Proc. IEEE Int.Conf.Information and Automation*, pp. 960–964, June 2012.

[13] J. Zhao, L. Jiang, H. Cai, H. Liu, "EMG pattern recognition method for prosthetic hand based on wavelet transformand sample entropy," *Control and Decision*, vol. 22, no. 8, pp. 927–930, Aug. 2007.

[14] G. Naik, D. Kumar, and S. Arjunan, "Use of sEMG in identification of low level muscle activities: Features based on ICA and fractal dimension," in *Proc. Ann. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pp. 364–367, Sep. 2009.