Classification of Mechanomyogram Signal Using Wavelet Packet Transform and Singular Value Decomposition for Multifunction Prosthesis Control

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Abstract: Previous works have resulted in some practical achievements for Mechanomyogram (MMG) to control powered prostheses. This work presents the investigation of classifying the hand motion using MMG signals for multifunctional prosthetic control. MMG is thought to reflect the intrinsic mechanical activity of muscle from the lateral oscillations of fibers during contraction. However, external mechanical noise sources such as movement artifact are known to cause considerable interference to MMG, compromising the classification accuracy. To solve this noise problem, we proposed a new scheme to extract robust MMG features by the integration of wavelet packet transform (WPT), singular value decomposition (SVD) and a feature selection technique based on distance evaluation criteria for the classification of hand motions. WPT was firstly adopted to provide an effective time-frequency representation of non-stationary MMG signals. Then, SVD and the distance evaluation technique were utilized to extract, select the optimal feature representing the hand motion patterns from the MMG time-frequency representation matrix. Experimental results of 12 subjects showed that four different motions of the forearm and hand could be reliably differentiated using the proposed method when two channels of MMG signals were used. Compared with three previously reported time-frequency decomposition methods, i.e., short-time Fourier transform (STFT), stationary wavelet transform (SWT), and S-transform (ST), the proposed classification system gave the highest average classification accuracy up to 89.7%. The results indicated that the MMG could potentially serve as an alternative source of electromyogram (EMG) for multifunctional prosthetic control using the proposed classification method.

Keywords: Mechanomyogram, electromyogram, muscle activity classification, wavelet packet transform, singular value decomposition, prosthetic control

1. **Introduction**

The Mechanomyography (MMG) is a recording of mechanical oscillation that is detectable on the body surface overlying the muscle. It is considered that the MMG is produced by lateral dimensional changes in active muscle fibers, which generate pressure waves, and reflects the mechanical activity of muscle (Barry and Cole 1990, Orizio 1993). It has been suggested that MMG is the mechanical counterpart of motor unit electrical activity as measured by electromyography (EMG) (Beck *et al* 2004). With the progress of MMG sensor and its detection techniques, recent studies have examined the MMG amplitude and frequency responses during maximal concentric and eccentric isokinetic muscle actions (Kouzaki and Fukunaga 2008, Ryan *et al* 2008) as well as maximal and sub-maximal cycle ergometry (Housh *et al* 2000, Perry *et al* 2001, Shinohara *et al* 1997). Clinically, MMG may be used as a diagnostic tool for neuromuscular diseases (Rhatigan *et al* 1986) including cerebral palsy (Akataki *et al* 1996), myotonic dystrophy (Orizio *et al* 1997), craniomandibular disorders (L'Estrange *et al* 1993), chronic and severe low back pain (Yoshitake *et al* 2001), diaphragmatic fatigue (Petitjean *et al* 1994). In addition, to achieve distinct hand postures, specific patterns of forearm muscle activity are required (Brochier *et al* 2004).

The MMG signal can provide information about various aspects of muscle activity including the number and firing rates of recruited motor units during voluntary isometric contraction (Orizio 2004). Therefore, it is conceivable that through a specific feature extraction and pattern recognition scheme, different types of muscle activity may be discernible via MMG signals for externally powered prosthetic control. Moreover, MMG offers a number of notable advantages over the conventional EMG, which has for many years been the mainstay of externally powered prosthesis. First, MMG signals propagate through soft tissue and so can be recorded distal to the activating muscle. This provides great flexibility in prosthetic design so that wires, sensors and electronics can be located away from the activating muscle, facilitating the use of more comfortable silicon soft sockets (Silva *et al*. 2004). Secondly, MMG is a mechanical signal, no skin preparation is required and it is not affected by changes in skin impedance due to sweating. Thirdly, with the use of soft-sockets facilitated by MMG, below-elbow amputees can retain natural forearm rotation which is hampered by current hard supracondylar sockets (Silva *et al*. 2005). Therefore, accurate and computationally efficient means of classifying MMG signal patterns has been a subject of effort in recent years.

The reported approaches to solve the motion command identification problem using MMG signals can be summarized as follows. Barry *et al*. (1986) used a standard microphone to collect MMG signals from human extensor digitorum and flexor digitorum muscles. They showed that the system could discriminate between wrist flexions and extensions using the amplitude of the MMG signals while exhibiting robustness to changes in sensor placement and skin impedance. Silva *et al*. (2004) designed a silicon-embedded microphone-accelerometer sensor pairs to record MMG signals and move limb motion artifacts. They used the root mean square (RMS) values of the segmented MMG signals as features and a two-category linear classifier to recognize open and close actions for a prosthetic hand. From the cross-validation tests, they obtained classification accuracy of approximately 70% for the two subjects tested. Subsequently, they improved their system with efficiently eliminating interference in the acquired signals and optimizing mechanical coupling (Silva *et al* 2005) and achieved a higher accuracy of 88% and 71% for the same two subjects. Compared to the EMG prosthetic control, the classification accuracy of MMG system is fairly low. EMG signals with time or time-frequency domain feature and linear discriminant analysis classifier can obtain higher than 90% accuracy rate (Englehart *et al* 1999, Parker *et al* 2006). In addition, many EMG controlled powered limb prostheses can provide controls with more than one degrees of freedom (DOF). However, the MMG control is still limited to single DOF (Barry *et al* 1986, Silva *et al* 2004, 2005).

Accordingly, the aim of the present paper is to explore the feasibility of identification of multiple hand motions by MMG signals for multifunctional prosthetic control with an improved rate of success. Thus, 2 channels of MMG signal acquired from extensor and flexor were used as the information source to differentiate 4 hand and wrist gestures. Most of the power of MMG signal resides between 5 to 100 Hz which is lower than that of EMG (Orizio 1993), though others reported with higher bandwidths (Beck *et al* 2005, Yoshitake *et al* 2002). It can be more easily contaminated by the limb movement artifact and environmental noises (Torres *et al* 2005), especially for the transient MMG. Instead of extracting transient

MMG feature to feed as the pattern classifier input, we adopted the steady MMG as information source for control purpose. Alves and Chau (2008) investigated the stationarity of steady state MMG signals for the purpose of determining appropriate features for signal classification. The results of a reverse arrangements test for stationarity indicated that, on average, 20% of the MMG signals recorded at three muscle sites during the performance of 6 different grasps were non-stationary. This suggests that the typical temporal or spectral features may have limited discriminatory power in multifunctional MMG pattern recognition for prosthetic control. So, an approximate time-frequency representation (TFR) method is desired to accommodate time-varying non-stationary MMG signal (Alves and Chau 2008). In this study we propose a wavelet packet transform (WPT) combined with singular value decomposition (SVD) feature extraction method. In addition, to eliminate the irrelevant feature associated to the limb artifact and noises, we adopted a distance evaluation technique to select the optimal singular values (SVs) that can well represent the hand motion patterns. The performance of the proposed method for MMG classification was evaluated in the context of a linear discriminant analysis (LDA) classifier. The block diagram schematic of the proposed MMG pattern recognition system is shown in Figure 1. The classification results were also compared with three other time-frequency decomposition based SVD feature extraction methods used before in EMG prosthetic control.

2. Methods

2.1 Experiments and data acquisition

This study attempted to recognize four kinds of hand-wrist motion: flexion and extension of the wrist, opening and grasping of the hand. Two acceleration sensors (EGAS-FS-10-V05, Measurement Specialties, Inc., Hampton, VA) were used to collect MMG signals, followed by a bandpass filter with a bandwidth of 5-400 Hz and an amplifier with a gain of 5000 provided by a custom-made device. The MMG signals were digitized by using an A/D converter board (NI PCI-6024E, National Instruments, Austin, USA), and the sample frequency was 1 kHz.

In the experiment, the MMG data were collected from twelve non-amputee subjects (eight males and four females with the age of 22-38). All the participants were right-hand-dominant without any known neuromuscular disorders. The human subject ethical approval was obtained from the relevant committee in the authors' institution and informed consents were obtained from all subjects prior to the experiment. Since hand motions result from contraction of the muscles in the forearm, two MMG sensors were placed on the extensor digitorum, flexor digitorum, respectively. The sensors were secured over the belly of the muscles with double-sided adhesive tape. The subject was asked to contract with a moderate force of approximately 50% to 70% of the maximum voluntary contraction (MVC) for each of the four motion patterns. No feedback was provided to regulate the force level and no load was applied during the actions. Each motion pattern was performed for a duration of 5 s, then switched to another motion in a random order until the four motion patterns were all performed. Finally, three repeated trials were conducted, together generating 60 s of data for each subject. The three repeated 20s dataset were used as training, validation, test dataset, respectively. The validation set provides an estimate of the classification performance of the test set. Consequently, the validation set was used to specify the dimensionality of the reduced feature set when using distance evaluation criteria, by prescribing the dimension at which the classification error was minimized.

2.2. *Wavelet packet transform*

As an extension of the standard wavelet, WPT represents a generalization of multi-resolution analysis and use the entire family of sub-band decomposition to generate an overcomplete representation of signals. WPT has recently been applied to various biomedical signal detection (Chendeb *et al* 2006, Gutierrez *et al* 2001), classification (Behroozmand and Almasganj 2007, Li *et al* 2005), compression (Hilton 1997, Martinez-Alajarin *et al* 2004) and noise reduction (Leman and Marque 2000) with great successes. Instead of dividing only the approximation spaces, wavelet packet bases present both approximation and detail spaces in a binary tree by recursive splitting of vector spaces. Any node of a binary tree is labeled by its depth j and number p of nodes (packets). Each node (j, p) corresponds to a space W_j^p, which admits an orthonormal basis $\{\Psi_j^p(n-2t)\}_{n\in Z}$. The two wavelet packet orthogonal bases at the children nodes are defined by the recursive relations:

$$\Psi_j^{2p-1}(t) = \sum_{n=-\infty}^{\infty} h[n]\Psi_{j-1}^{p}(n-2t) \quad (1)$$

And

$$\Psi_j^{2p}(t) = \sum_{n=-\infty}^{\infty} g[n]\Psi_{j-1}^{p}(n-2t) \quad (2)$$

Two orthogonal spaces W_j^{2p} and W_j^{2p-1} can be defined as closure spaces of time-varying signal $x_j^{2p}(k)$ and $x_j^{2p-1}(k)$, respectively. Meanwhile, they can also be represented as:

$$W_j^{p} = W_j^{2p} \oplus W_j^{2p-1} \quad (3)$$

This recursive splitting defines a binary tree of wavelet packet spaces where each parent node is divided into two orthogonal subspaces. When domain signal $x(t)$ satisfies two-scale relations:

$$\begin{aligned} x_{j+1}^{2p}(t) &= \sqrt{2}\sum h(n)x_{j+1}^{2p}(2t-n) \\ x_{j+1}^{2p+1}(t) &= \sqrt{2}\sum g(n)x_{j+1}^{2p}(2t-n) \end{aligned} \quad (4)$$

where $g(n) = (-1)^n h(1-n)$, i.e. $g(n)$ is orthogonal with $h(n)$.

The expanding coefficients $h[n]$ and $g[n]$ can be expressed in frequency domain as

$$H\{\cdot\} = \sum_{n=-\infty}^{\infty} h(n-2t) \quad G\{\cdot\} = \sum_{n=-\infty}^{\infty} g(n-2t) \quad (5)$$

Let $x_j^p(k)$ be the *p*th packet on *j*th resolution, hence, the wavelet packet transform can be computed by the following recursive algorithm

$$\begin{aligned} & x_0^1(k) = x(t) && x_j^{2p-1}(k) = Hx_{j-1}^{p}(k) \\ & x_j^{2p}(k) = Gx_{j-1}^{p}(k) && x_j^{p}(k) = x_j^{2p-1}(k) + x_j^{2p}(k) \end{aligned} \quad (6)$$

Where $k = 1, 2, \cdots, 2^{J-p}$, $p = 1, 2, \cdots, J$, and $J = \log_2 N$

In the present study, the MMG signal was decomposed into level 5 and the wavelet packet decomposition tree was shown in Figure 2. The MMG signal wavelet packet representation matrix was constructed as follows

$$X = [x_5^1(k); x_5^2(k); \cdots x_5^{32}(k)] \quad (7)$$

2.3. Singular value decomposition

The MMG signal presentation matrix based on WPT produces a large amount of coefficients, sometimes even larger than the original data points. So, a scheme of feature extraction is necessary to make the classifier simpler and enable the methodology for real time applications. This approach was performed by SVD in the present study. The singular value decomposition of a matrix provides a robust, numerically reliable and efficient technique for feature extraction and dimension reduction (Hassanpour *et al* 2004, Lukasik 2005). A SVD of the $M \times N$ matrix X described in Equation (7) was given by

$$X = U \Sigma V^T \quad (8)$$

Where U ($M \times M$) and V ($N \times N$) are orthonormal matrices, and Σ is a $M \times N$ diagonal matrix of singular values ($\sigma_{ij} = 0$ if $i \neq j$ and $\sigma_{11} \geq \sigma_{22} \geq \cdots \geq 0$)

2.4. Distance evaluation technique for feature selection

In the previous study of SVD-based feature for pattern recognition, most researchers employed the whole or just the several larger SVs as the pattern feature (Cai *et al* 1999, Gu *et al* 2002, Lukasik 2005, Marinovic and Eichmann 1985). However, the SVs extracted from the MMG wavelet packet decomposition include not only the information about the muscle fiber vibration during different contraction pattern, but also the information about the gross movement of the muscle or the limb movement and even the white noise. The latter features, which are not able to classify MMG signal patterns, will deteriorate the classification accuracy. So, it would not be appropriate to input the whole or just the several larger SVs to the MMG classifier. To select the optimal features that can accurately distinguish one MMG signal pattern from the others, a feature selection method based on the distance evaluation technique was presented (Widodo *et al* 2007, Yang *et al* 2004).

Suppose that the joint feature set of c hand motion patterns $\omega_1, \omega_2, \cdots, \omega_c$ is

$$\{q^{(i,k)}, i = 1, 2, \cdots, c; k = 1, 2, \cdots, N_i\}$$

Where $q^{(i,k)}$ is the kth feature of ω_i , and N_i is the number of feature in ω_i .

The average distance of all features in ω_i , can be determined as follows:

$$D_i = \frac{1}{2}\frac{1}{N_i}\sum_{j=1}^{N_i}\frac{1}{N_i - 1}| q^{(i,j)} - q^{(i,k)} | \quad (9)$$

The average distance of D_i ($i = 1, 2, \cdots, c$) is

$$D_a = \frac{1}{c}\sum_{i=1}^{c} D_i \qquad (10)$$

Substituting Eq. (9) into Eq. (10) yields

$$D_a = \frac{1}{c}\sum_{i=1}^{c} \frac{1}{N_i - 1}\sum_{k=1}^{N_i} | q^{(i,k)} - \rho^{(i)} | \qquad (11)$$

Where

$$\rho^{(i)} = \frac{1}{N_i}\sum_{k=1}^{N_i} q^{(i,k)} \qquad (12)$$

is the mean of all features in ω_i .

The average distance of c different motion patterns $\omega_1, \omega_2, \cdots, \omega_c$ is

$$D_b = \frac{1}{c}\sum_{i=1}^{c} | \rho^{(i)} - \rho | \qquad (13)$$

Where

$$\rho = \frac{1}{c}\sum_{i=1}^{c} \frac{1}{N_i}\sum_{k=1}^{N_i} q^{(i,k)} \qquad (14)$$

is the mean of all the features in all c motion patterns.

When the average distance D_a inside certain motion pattern is smaller and the average distance between different motion patterns is bigger, the average represents the optimal features well. The evaluation criteria for optimal features is defined as

$$F = \frac{D_b}{D_a} \qquad (15)$$

So the optimal SVs for motion pattern classification can be selected from the original SVD feature sets according to the bigger distance evaluation measure F .

2.5. Training parameters, classifier and statistical analysis

Optimization of transform parameters was done empirically, by selecting the methods that subtend the best generalization performance, on average, across all subjects. The selection of mother wavelet type was made amongst all possible orders of the following families: Daubechies, Coiflet, Symmlet, Myer and biorthogonal spline (Daubechies 1992). Coiflet-4 was chosen as mother wavelet due to its power to minimize the test set classification error. The class separability based objective functions was selected as the WPT cost function amongst several criteria (Saito and Coifman 1995).

Since the emphasis of this paper is not upon the classifier, the performance of the proposed MMG classification system was evaluated in the context of a linear discriminant analysis (LDA) classifier (Duda *et al* 2001). The LDA is easily implemented, much faster to train, and well understood representatives of statistical classifiers. To illustrate the classification performance of the proposed method, we compared the method with three other time-frequency decomposition, i.e., short-time Fourier transform (STFT), stationary wavelet transform (SWT), and S-transform (ST), combined with SVD methods. The STFT, also known as the Windowed Fourier Transform or spectrogram, is a development that extends standard Fourier transform techniques to handle non-stationary data (Hardalac *et al* 2007). Fourier transforms are applied to short windows of data. These windows are moved along the data and may overlap. The STFT gives information for a fixed frequency and time resolution dependent on the window. The SWT is an offshoot of the discrete wavelet transform whereby the scales are dyadic but the time steps are not sub-sampled at each level and hence are not dyadic (Addison 2005). The S-transform is another approach of time-frequency representation of a signal. It is an invertible time-frequency spectral localization technique that combines elements of wavelet transforms and STFT (Stockwell *et al* 1996). The analyzing window of the ST is a scaled Gaussian, whose width scales inversely, and whose height scales linearly with the frequency. This scaling, similar to the case in wavelet, improves the time resolution of high frequency events, and the frequency resolution of low frequency events, in comparison of the STFT, while maintaining the absolute phase of each frequency component in contrast with the continuous wavelet transform's. The STFT and SWT have previously applied to EMG based hand and forearm motion classification for prosthetic control (Cai *et al* 1999, Monfared and Setarehdan 2006) and ST-SVD for other bio-signal feature extraction (Assous *et al* 2006). Different from the WPT based method, the matrix used for SVD in each of the three methods is just the time-frequency representation matrix $X(t, f)$. Then, the SVD, feature selection from the SVs, and LDA classification procedures were also applied to the three methods as in the proposed system.

To statistically compare the performances among the three methods, a one-way Analysis Of Variance (ANOVA) was performed (Castillo-Valdivieso *et al* 2002).

3. Results

The typical MMG signals acquired from subject 3 was shown in Figure 3. The MMG training set data for each duration of 5s were divided into discrete 256-sample epochs and inputted to the proposed classifier. The segment in the end of each motion which was not long enough to 256-sample was omitted in order to improve the quality of training data. Using the wavelet packet transform parameters specified above, the SVs of each motion pattern of every data epoch could be obtained. Figure 4 shows the typical SVs of four motion patterns of subject 3. It could be seen that 30 SVs were resulted from the wavelet packet decomposition into level 5 (Figure 4). The results of feature selection using distance evaluation technique for the above SVs are shown in Figure 5. It is notable that some larger SVs did not carry more motion pattern information with higher distance evaluation index F . On the contrary, the SVs with higher F value are not always the larger SVs. Similar results were obtained for all other subjects.

Due to the use of different time-frequency representation method, the numbers of SVs obtained from STFT, SWT, and ST decomposition were different and they were 10, 9, and 26, respectively. However, the F value distributions of SVs of the three methods (Figures 6, 7 and 8) were similar to that of the WPT-SVD method. Compared them with Figure 5, it could be seen that the F values of several SVs of WPT were higher than the maximum F value of SVs of other three methods. This means that the feature extracted by WPT-SVD carried more motion pattern information than those obtained by the other methods. Figure 9 shows the training sample scatter plot of the optimal SV of each channel obtained using the four different methods. Obviously, the optimal SVs of WPT held better class separability among the four methods.

After the distance evaluation index F of each SV was computed, the SVs were reassigned in the order from larger to lower F value. Then, different dimensional eigenvector was constructed according to the following rule, i.e., the first eigenvector was constructed by the SV with maximum F in each of two channels, the second eigenvector was constructed by the SVs with maximum and second-maximum F in each of two channels, till the last one, composed by the all SVs of two channels. These eigenvectors with different dimensions were then provided to train the LDA classifier. After the classifiers were trained, the validation set was used to determine the optimal eigenvector dimension for different methods. The effect of eigenvector dimension upon the validation set classification accuracy is shown in Figure 10. All methods share the similar law, i.e. showing fluctuated responses. The accuracy increased at small numbers of SVs and then reached highest. Further increase in SVs number does decrease the accuracy of the classifiers.

Then, for each subject, the best dimension was selected to minimize the validation set error, and the classification accuracy on the test set was evaluated at this dimension. Figure 11 depicts the classification accuracy of the test set of all subjects. The corresponding averaged accuracy of WPT, STFT, SWT, ST method was 89.7%, 80.9%, 81.8%, and 85.6%, respectively. The results indicated that the hand motion pattern could be recognized by different time-frequency decomposition combined SVD feature extraction method. One-way ANOVA was used to compare the performance of the four methods. The results are shown in Table 1. The proposed method achieved significant improvement in classification accuracy as compared with the STFT (p = 0.0001), SWT (p = 0.0018), and ST (p = 0.0384) method. Meanwhile, the results indicated a distinct trend toward improvement in the progression of STFT→SWT→ST→WPT.

For a real-time prosthetic control, the *response time* of a control system should not introduce a delay that is perceivable by the user. The time threshold for acquiring the data plus the processing time of generating classified control commands is generally regarded to be roughly 300 ms (Parker *et al* 2006). The processing delays were empirically evaluated using a 2.2-GHz Intel-based computer. The computation was performed in Matlab (Version 8.0, The Mathworks, Natick, MA, USA) and the matrix multiplications were built-in functions. Table 2 shows the processing delay of each stage required using four different methods. Though the high-speed microprocessors could reduce the computing time in real control system, the result demonstrated that the WPT and STFT methods were computation saving, while the SWT and ST methods were rather time consuming.

4. Discussion and conclusions

The MMG represents a compound signal generated by the activation of many motor units that are summated at the skin's surface. Under voluntary conditions, the asynchronous activity of motor units that contribute to the MMG signal may contain information regarding motor control strategies (Orizio *et al* 1997, Petitjean and Bellemare 1994). The amplitude of the MMG signal may contain information regarding motor unit recruitment as well as the active stiffness of skeletal muscle during the fusion of twitches (Orizio *et al* 2003). The bandwidth of the MMG signal is normally considered between 5Hz to 100Hz (Orizio 1993), while higher cutoff frequencies are used by some researchers (Beck *et al* 2005, Yoshitake *et al* 2002) . It contains the low frequency component with bigger amplitude due to gross movement of the muscle or body and other noises. So, it is not approximate to use the time domain feature, i.e., mean absolute value (MAV), zero crossing (ZC), etc, as pattern classifier input, which gave great success in EMG prosthetic control (Hudgins *et al* 1993). Although not directly verified, it has also been suggested that the MMG power density spectrum provides qualitative information regarding the global firing rate of the unfused activated motor units (Akataki *et al* 2001, Orizio *et al* 2003). So, it is feasible to distinguish hand movements with different motor control strategies from MMG frequency domain parameters. In the present work, wavelet packet transform was applied as the MMG feature extractor due to its non-stationarity (Alves and Chau 2008).

The previous works on the achievements of MMG powered prosthesis were limited to single DOF. The main contribution of the present work is to confirm the potential of MMG signals for practical prosthetic control with multiple control outputs (i.e., >2). Furthermore, the results reaffirm that information about the muscle activity similar to that obtained by conventional EMG sensors can be extracted from MMG signals.

To achieve the goal of multiple degrees of motion using MMG classification, we proposed a new approach to construct time-frequency representation matrix from the redundant wavelet packet decomposition coefficients. The SVD of a matrix provides a robust numerically reliable and efficient technique for feature extraction. The SVs of the SVD are stable, rotation and ratio invariant, and thus was employed to the wavelet packet coefficient matrix for feature extraction. After processed by SVD method, sometimes there are still high noises, irrelevant or redundant information in this extracted SVs. Different from the previous study to use the whole or some larger SVs directly as the classifier input (Cai *et al* 1999, Monfared and Setarehdan 2006), a distance based feature selection scheme was then employed to select the most discriminable SVs. The results on validation set indicate that this step can improve the classification accuracy significantly. Moreover, the benefits of this procedure include a reduction in the amount of data needed to achieve learning and reducing executive time.

To compare the performance of the proposed method, the classification results of STFT, SWT, and ST combined with SVD, which have been employed in muscle activity classification using EMG signals or other biosignal analysis, were also obtained. The proposed method demonstrates an obvious advantage to the others upon classification accuracy. The reason for the superiority of WPT-SVD to others is that WPT provides an overcomplete set of adaptive time-frequency tilings of the MMG signal and the best one which maximizes the class separability is selected. In the analysis of signals in the time-frequency domain using SVD, the type of time-frequency distribution is important (Assous *et al* 2006). Indeed, it is desirable that the TFR is linear and has high resolution, which is the case of the WPT. Another interesting finding in the work is that the accuracy of ST is superior to SWT and STFT, though not as good as WPT. In essence, the ST is a special continuous wavelet transform, which allows arbitrarily high resolution of the signal in the time-frequency plane (Assous *et al* 2006). On the other hand, SWT is a special discrete wavelet transform, which produces few coefficients but exhibits coarse time-frequency resolution (Monfared and Setarehdan 2006). In addition, it is well known that the STFT has a fixed tiling when partition the time-frequency plane; once specified, each cell has an identical aspect ratio (Englehart *et al* 1999). These factors may cause the significant difference in their classification errors among ST and SWT, STFT.

Besides the accuracy of movement selection, the response time is another important aspect of prosthetic controllability. The SWT does not decimate the signal at each stage, as does the standard discrete

WT and WPT. This avoids the problem of nonlinear distortion of the WT and WPT with shifts in the signal, at the expense of more computational effort. In addition, the ST is represented as a continuous wavelet transform (CWT) with a specific mother wavelet multiplied by the phase factor. So, the computation burdens of them are both larger than WPT and STFT. On the other hand, though the time consuming of STFT is the lowest among them, the success rate of motion recognition is the worst. Overall, the WPT-SVD is the best choice for MMG pattern classification with the highest accuracy and low processing delays. It offers an alternative approach for analyzing MMG signals in different applications, such as differentiating a concentric muscle action from an eccentric muscle action. It would be also a potential new technique to be applied to other noisy bio-signals (such as EMG) to improve the accuracy of the decisions made for prosthetic control. However, this need to be explored in the future work because the performances of pattern recognition techniques are sometimes closely related to the features of the signal under investigation.

A MMG signal comprises two states: (i) a transient state emanating from a burst of fibers, as a muscle goes from rest to a voluntary contraction level and (ii) a steady state emanating during a constantly maintained contraction in a muscle. The main weakness of using a transient state in MMG control is that contractions should be initiated from rest state. This prohibits switching from class to class in an effective or intuitive manner, and impedes the coordination of complex tasks involving multiple DOFs. Therefore, we consider the application of a steady-state MMG signal for real-time prosthetic control in the present work. In EMG prosthesis control, the steady-state data is classified more accurate than transient data, and classification suffers less degradation with shorter segment lengths (Parker *et al* 2006). The rate of classification degrades more quickly as the segment length of transient data is decreased, than with steady-state data. Therefore, steady-state data with a shorter segment length, such as 128 ms, is more reliable if a faster system response is required (Parker *et al* 2006). It is desired to explore whether the steady-state MMG also exhibits this superiority to transient-state MMG in the future work.

Previous works have resulted in some practical achievements for MMG powered single DOF prostheses. In the present work, we have demonstrated the feasibility of MMG signal for multi-function prosthetic control. There are many papers that have examined the force-related patterns of response for the MMG signal, and most of these papers indicated that the relationship between MMG (time and/or frequency domains) was nonlinear (Akataki *et al* 2001, Mamaghani *et al* 2002, Madeleine *et al* 2006). Therefore, there may be an optimal amount of contraction force that may improve or reduce the classification accuracy of the WPT-SVD technique. This needs to further investigated in future studies with better-controlled contraction strengths. EMG has been widely used as an information source for human-machine interface. In the future work, measuring MMG and EMG signals simultaneously to extract more information related to muscle states should be explored to recognize more motions to make the prosthesis more flexible. In addition, other machine learning method, such as neural network, fuzzy logic, support vector machine, should be compared with LDA classifier for more accurate identification of motion so as to control prostheses more accurately and with more degrees of freedom.

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Figure captions:

Figure 1. The block diagram of the proposed MMG pattern classification system

Figure 2. Wavelet packet decomposition tree for the MMG signal

Figure 3. The typical MMG signals of four different motions acquired from subject 3

Figure 4. The SVs of MMG signal time-frequency representation matrix obtained from WPT for subject 3

Figure 5. Distance evaluation of SVs obtained from WPT for subject 3

Figure 6. Distance evaluation of SVs obtained from STFT for subject 3

Figure 7. Distance evaluation of SVs obtained from SWT for subject 3

Figure 8. Distance evaluation of SVs obtained from ST for subject 3

Figure 9. The scatter plot of the optimal SV of channel 1, 2 obtained by wavelet packet transform (WPT-SVD), short-time Fourier transform (STFT-SVD), stationary wavelet transform (SWT-SVD), and S transform (ST-SVD) method (subject 3)

Figure 10. The effect of SV number upon the validation set classification accuracy. The response is shown for the wavelet packet transform (WPT), short-time Fourier transform (STFT),, stationary wavelet transform (SWT) and S transform (ST) of subject 3

Figure 11. The classification accuracy of each subject and the averaged accuracy (black line) upon the test set using wavelet packet transform (WPT), short-time Fourier transform (STFT),, stationary wavelet transform (SWT) and S transform (ST) method

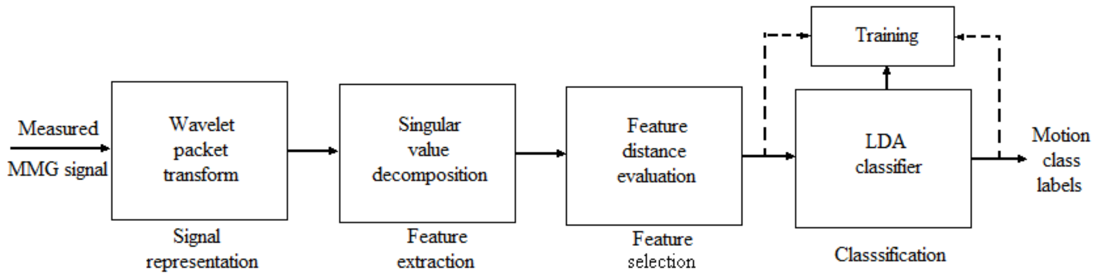
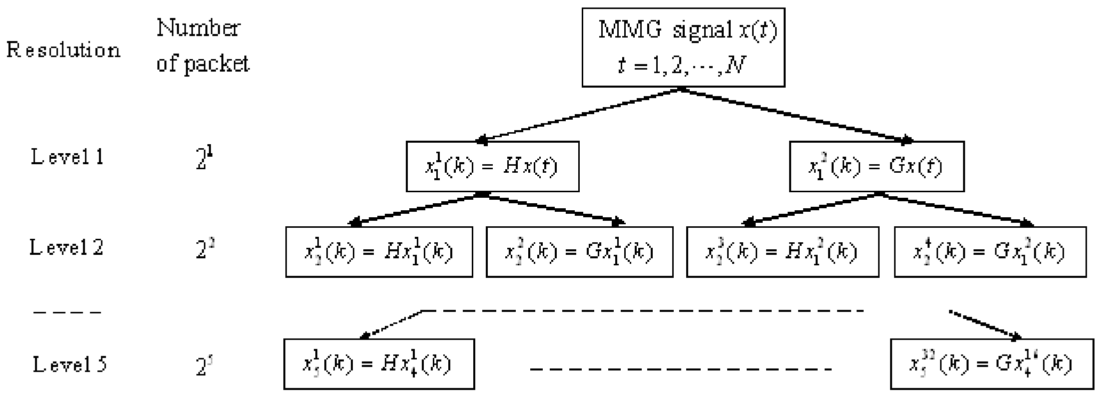


Figure 1.



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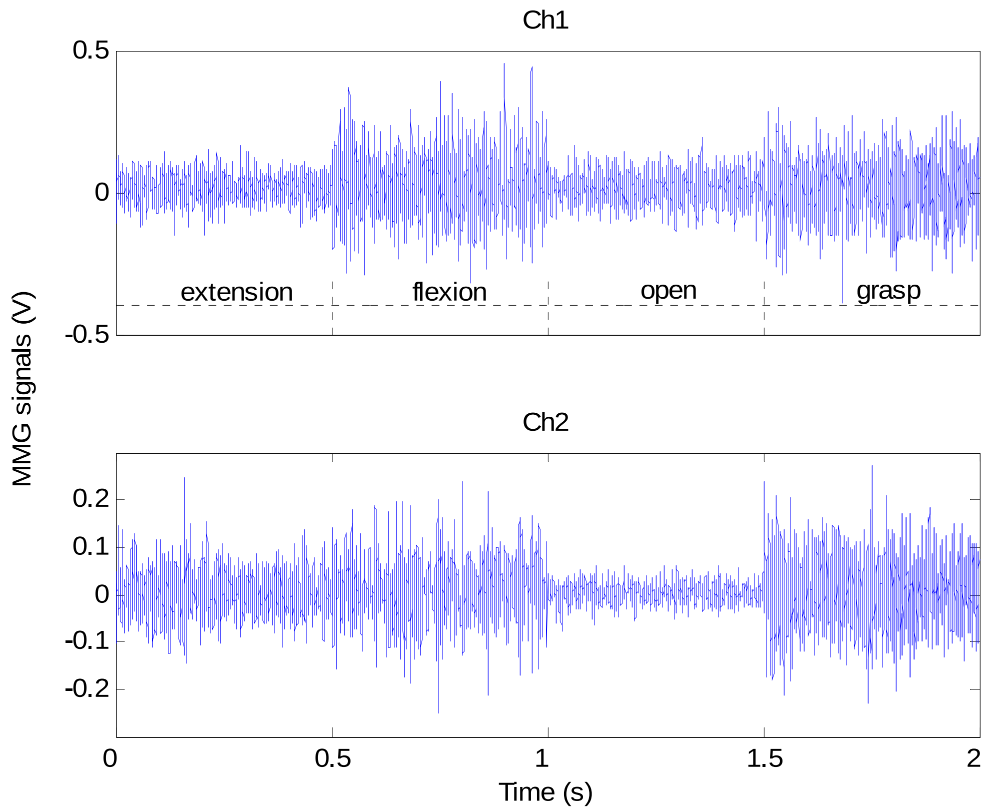
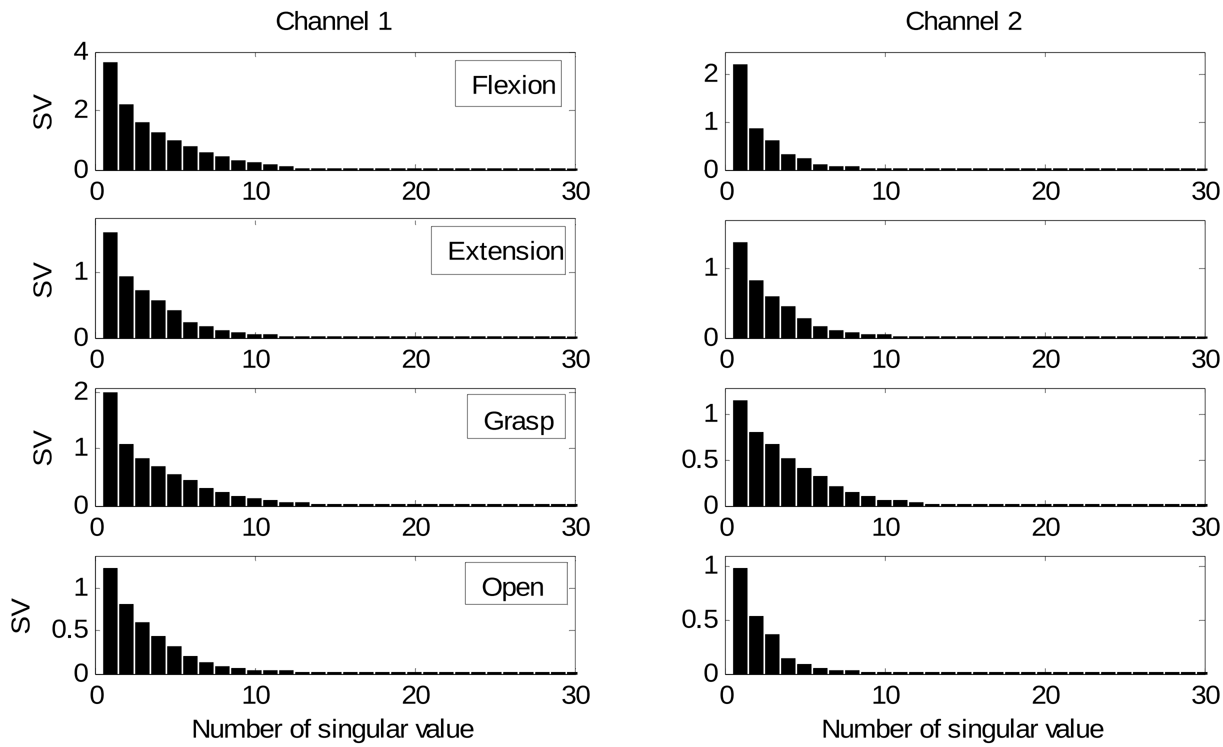

Ch1
0.5
0
-0.5
extension
flexion
open
grasp
MMG signals (V)
Ch2
0.2
0.1
0
-0.1
-0.2
0
0.5
1
1.5
2
Time (s)

Figure 3.



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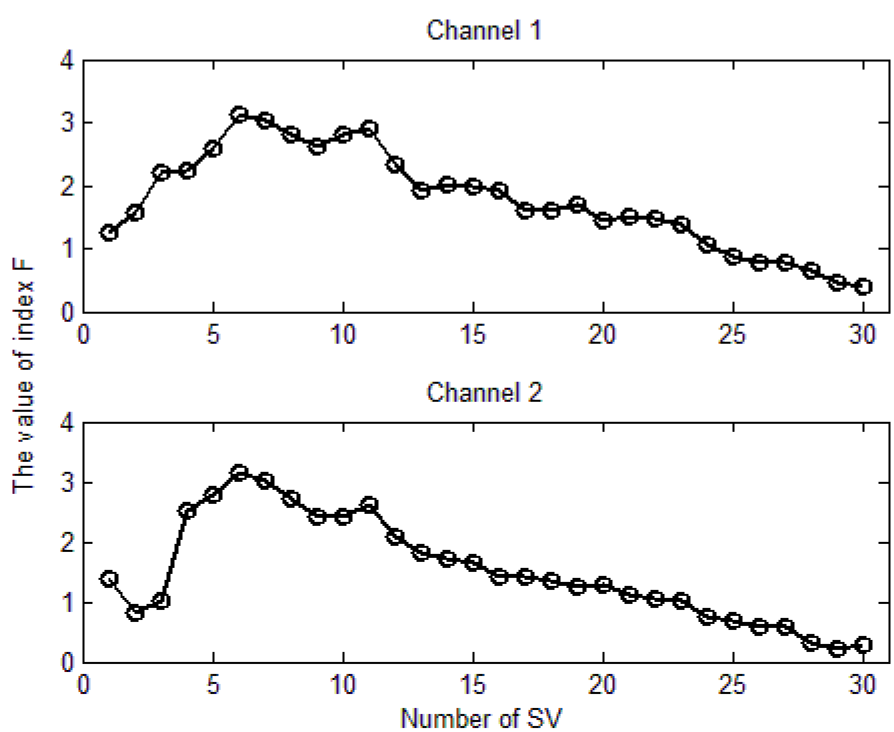

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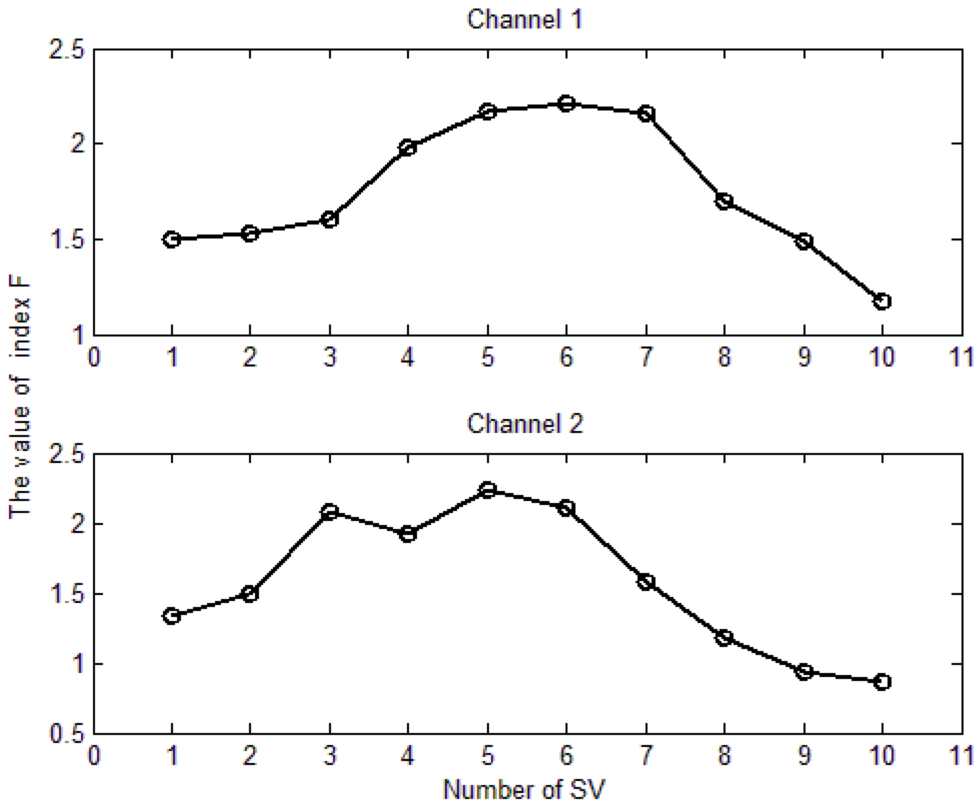
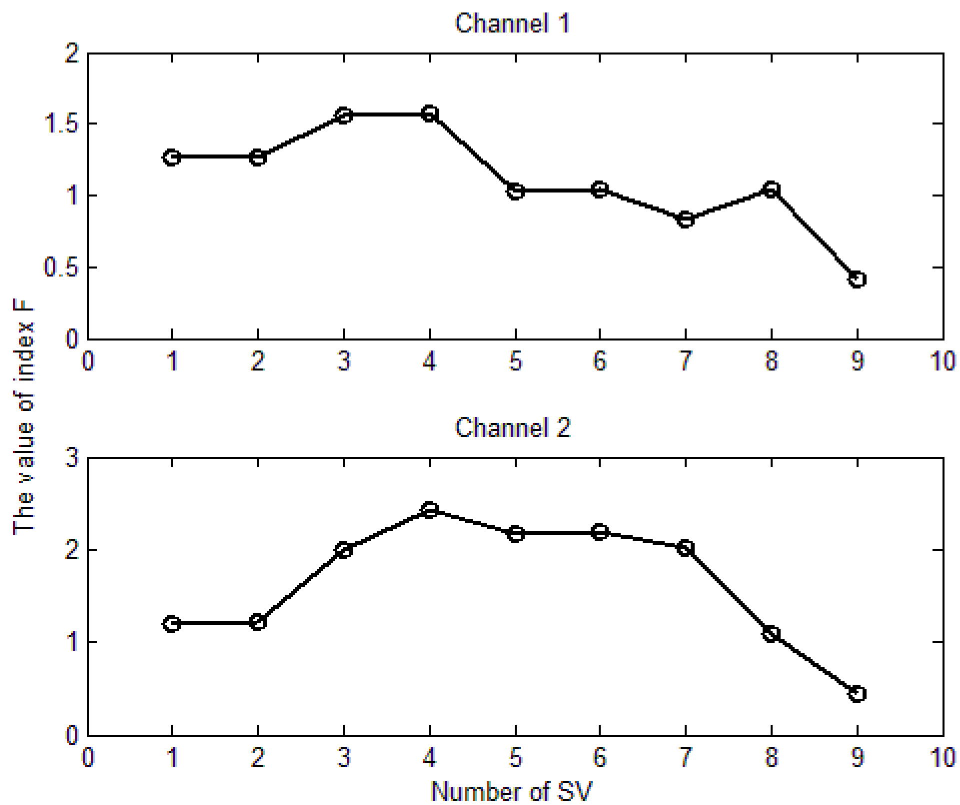

Channel 1
2.5
2
1.5
1
0
1
2
3
4
5
6
7
8
9
10
11
The value of index F
Channel 2
2.5
2
1.5
1
0.5
0
1
2
3
4
5
6
7
8
9
10
11
Number of SV

Figure 6.


Channel 1
Channel 2
The value of index F
Number of SV
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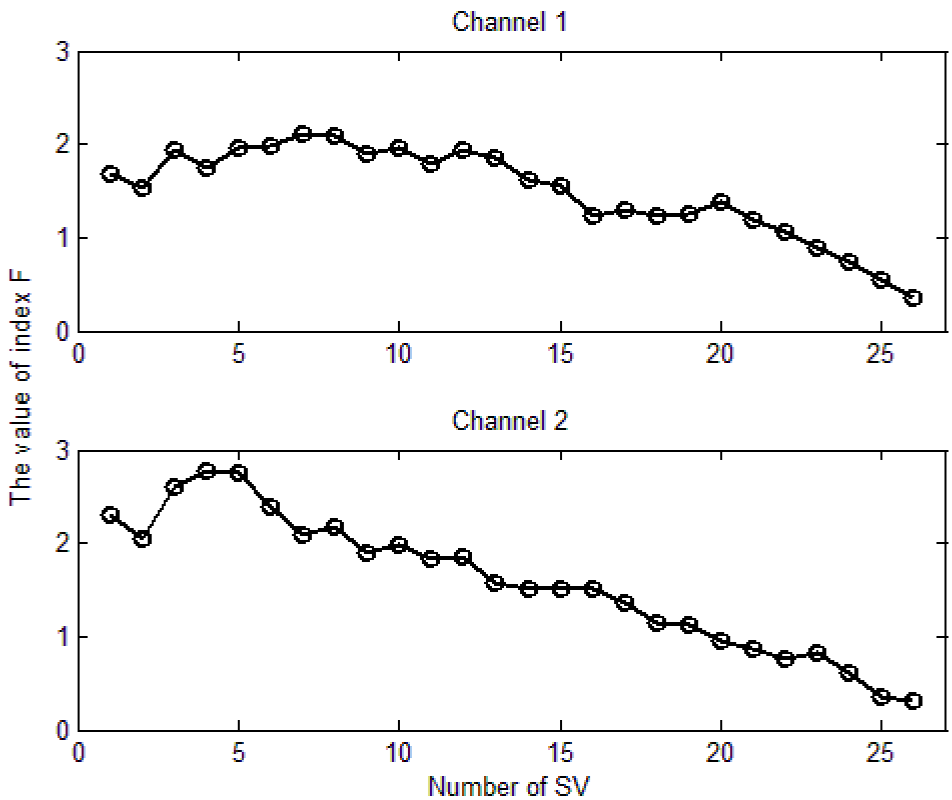
0.5
1
1.5
2
3
0 1 2 3 4 5 6 7 8 9 10

Figure 7.



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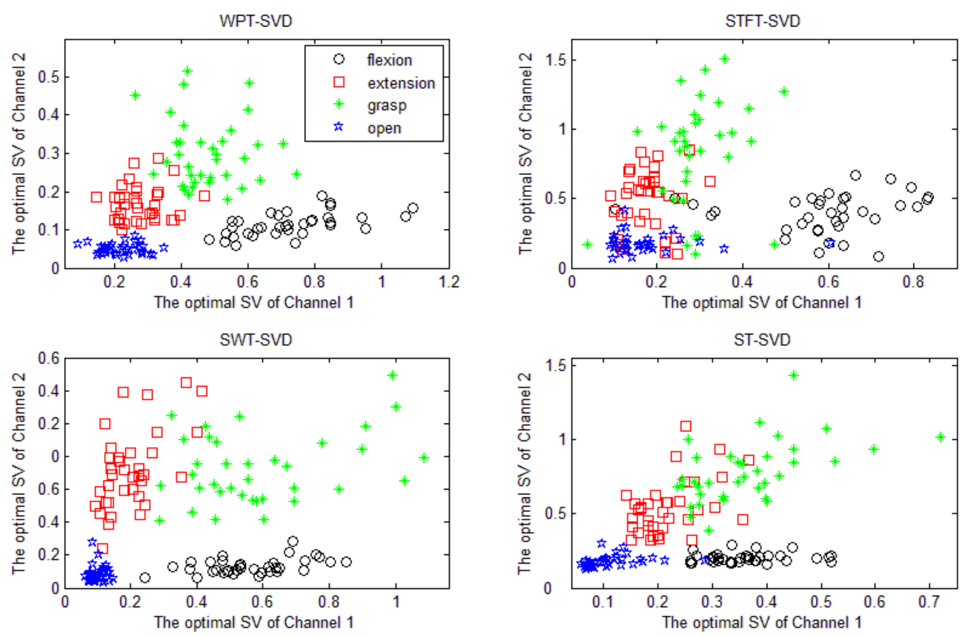

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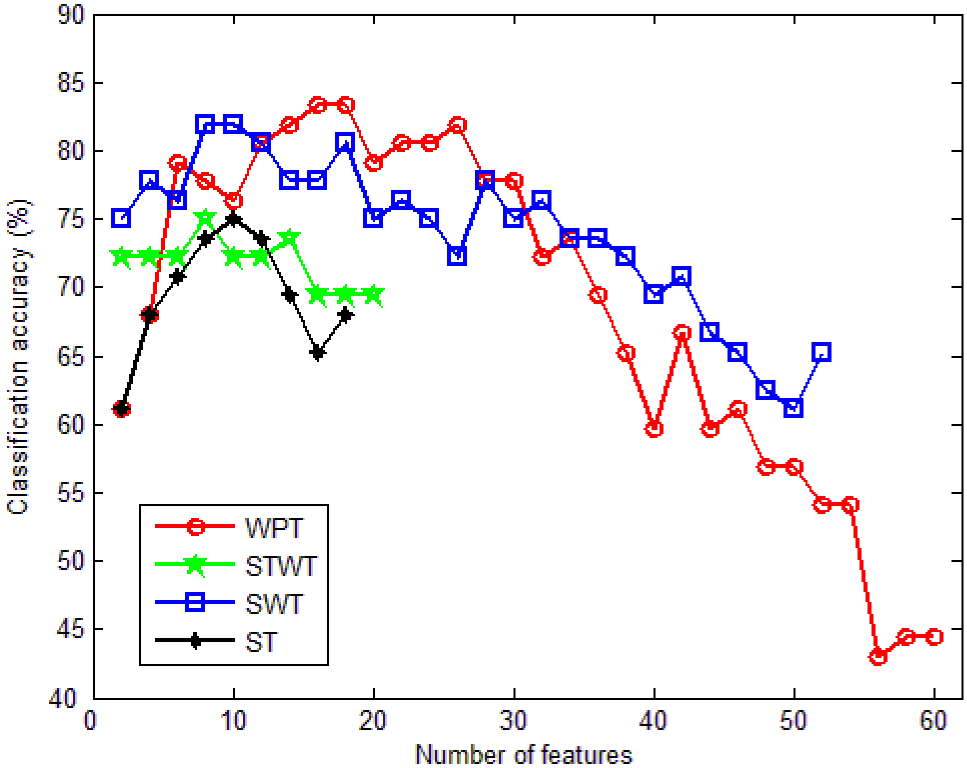

90
85
80
75
70
65
60
55
50
45
40
Classification accuracy (%)
0
10
20
30
40
50
60
Number of features
WPT
STWT
SWT
ST

Figure 10.

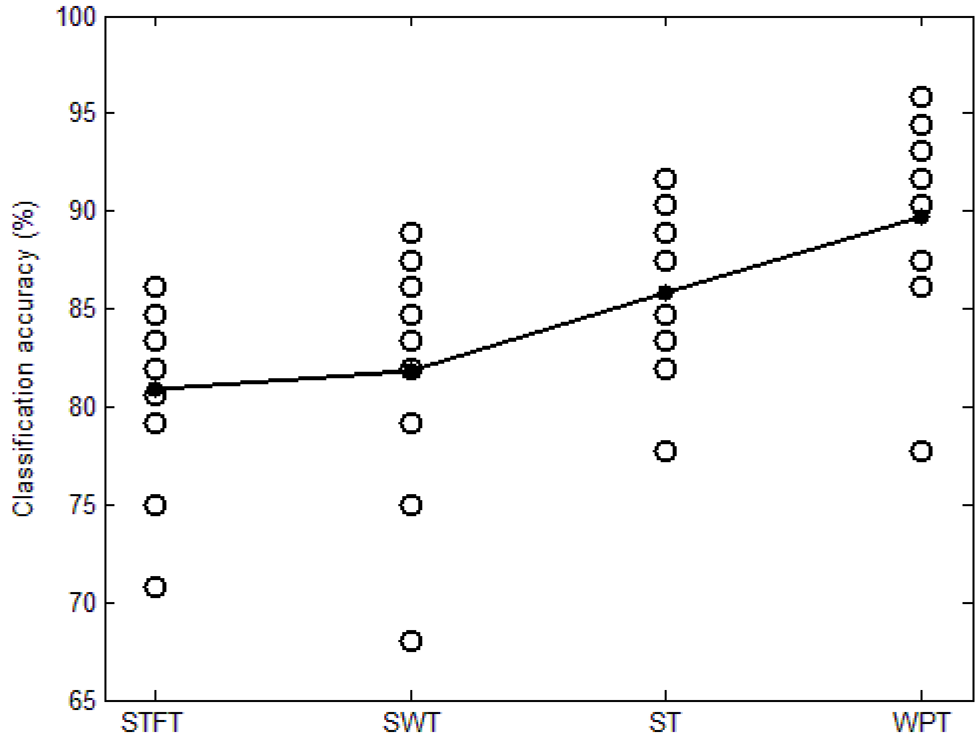
100
95
90
85
80
75
70
65
Classification accuracy (%)
STFT
SWT
ST
WPT

Figure 11.

Table captions:

Table 1. The results of one-way ANOVA for the classification accuracy of all subjects among the WPT, STFT, SWT, and ST combing SVD methods

Table 2. The processing delays associated with the signal representation, SVD, and LDA stages of the system using WPT, STFT, SWT, and ST decomposition method.

Table 1.

Method	WPT-SVD	STFT-SVD	SWT-SVD	ST-SVD
WPT-SVD	—	0.0001	0.0018	0.0384
STFT-SVD	0.0001	—	0．6619	0.0102
SWT-SVD	0.0018	0.6619	—	0.073
ST-SVD	0.0384	0.0102	0.073	—

Table. 2

Processing delay (ms)	WPT	STFT	SWT	ST
TF representation	41	2	195	128
SVD	2	2	2	2
LDA	1	1	1	1
Total	44	5	198	131