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Classification of the mechanomyogram signal using a 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 a 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 the wavelet packet transform (WPT), singular value decomposition (SVD) and a feature selection technique based on distance evaluation criteria for the classification of hand motions. The WPT was first adopted to provide an effective time–frequency representation of non-stationary MMG signals. Then, the SVD and the distance evaluation technique were utilized to extract and 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, stationary wavelet transform and S-transform, the proposed classification system gave the highest average classification accuracy up to 89.7%. The results indicated that MMG could potentially serve as an...

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alternative source of electromyogram for multifunctional prosthetic control using the proposed classification method.

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

(Some figures in this article are in colour only in the electronic version)

1. Introduction

Mechanomyography (MMG) is a recording of mechanical oscillation that is detectable on the body surface overlying the muscle. It is considered that MMG is produced by lateral dimensional changes in active muscle fibers, which generates pressure waves and reflects the mechanical activity of the 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 the MMG sensor and its detection techniques, recent studies have examined the MMG amplitude and frequency responses during maximal concentric and eccentric isokinetic muscle actions (Beck 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) and diaphragmatic fatigue (Petitjean and Bellemare 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 the 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, the 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). Second, MMG is a mechanical signal, no skin preparation is required and it is not affected by changes in skin impedance due to sweating. Third, 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 the MMG signal patterns have been a subject of much effort in recent years.

The approaches reported to solve the motion command identification problem using the MMG signals can be summarized as follows. Barry et al (1986) used a standard microphone to collect the 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 pair to record the 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 the open and close actions for a prosthetic hand. From the cross-validation tests, they obtained a classification accuracy of approximately 70% for the two subjects tested. Subsequently, they improved their system by 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 EMG prosthetic control, the classification accuracy of the MMG system is fairly low. EMG signals with a time or time–frequency domain feature and a linear discriminant analysis (LDA) classifier can obtain a 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, MMG control is still limited to a 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 the MMG signals for multifunctional prosthetic control with an improved rate of success. Thus, the two channels of the MMG signal acquired from an extensor and flexor were used as the information source to differentiate four hand and wrist gestures. Most of the power of the MMG signal resides between 3 and 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 a transient MMG feature to feed as the pattern classifier input, we adopted the steady MMG as the information source for the control purpose. Alves and Chau (2008) investigated the stationarity of the steady-state MMG signals for the purpose of determining appropriate features for signal classification. The results of a reverse arrangement test for stationarity indicated that, on average, 20% of the MMG signals recorded at three muscle sites during the performance of six 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 a time-varying non-stationary MMG signal (Alves and Chau 2008). In this study, we propose a wavelet packet transform (WPT) combined with a singular value decomposition (SVD) feature extraction method. In addition, to eliminate the irrelevant feature associated with 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 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.

Figure 1. The block diagram of the proposed MMG pattern classification system.
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, and opening and grasping of the hand. Two acceleration sensors (EGAS-FS-10-V05, Measurement Specialties, Inc., Hampton, VA) were used to collect the 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, TX), and the sample frequency was 1 kHz.

In the experiment, the MMG data were collected from 12 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 consent was obtained from all subjects prior to the experiment. Since hand motions result from the contraction of the muscles in the forearm, two MMG sensors were placed on the extensor digitorum and flexor digitorum, respectively. The sensors were secured over the belly of the muscles with a double-sided adhesive tape. The subject was asked to contract with a moderate force of approximately 50–70% 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 and then switched to another motion in a random order until all the four motion patterns were performed. Finally, three repeated trials were conducted, together generating 60 s of data for each subject. The three repeated 20 s datasets were used as training, validation and test datasets, 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, the WPT represents a generalization of multi-resolution analysis and use the entire family of sub-band decomposition to generate an overcomplete representation of signals. The WPT has recently been applied to various biomedical signal detection (Chendeb et al 2006), classification (Behroozmand and Almasganj 2007), compression (Martinez-Alajarín and Ruiz-Merino 2004) and noise reduction (Leman and Marque 2000) with great success. 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 \( \{ \Psi^j_p(n - 2t) \}_{n \in \mathbb{Z}} \). The two wavelet packet orthogonal bases at the children nodes are defined by the recursive relations

\[
\Psi^j_{2p-1}(t) = \sum_{n=-\infty}^{\infty} h[n] \Psi^j_{2p-1}(n - 2t)
\]

and

\[
\Psi^j_{2p}(t) = \sum_{n=-\infty}^{\infty} g[n] \Psi^j_{2p-1}(n - 2t).
\]
Two orthogonal spaces $W^{2p}_j$ and $W^{2p-1}_j$ can be defined as closure spaces of time-varying signals $x^{2p}_j(k)$ and $x^{2p-1}_j(k)$, respectively. Meanwhile, they can also be represented as

$$W^p_j = W^{2p}_j \oplus W^{2p-1}_j. \quad (3)$$

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

$$x^{2p+1}_{j+1}(t) = \sqrt{2} \sum h(n)x^{2p}_{j+1}(2t - n)$$  
$$x^{2p+1}_{j+1}(t) = \sqrt{2} \sum g(n)x^{2p-1}_{j+1}(2t - n), \quad (4)$$

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 the 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 $x^p_j(k)$ be the $p$th packet on the $j$th resolution; hence, the wavelet packet transform can be computed by the following recursive algorithm:

$$x^p_1(k) = x(t), \quad x^{2p-1}_j(k) = Hx^{p-1}_{j-1}(k),$$  
$$x^{2p}_j(k) = Gx^{p}_j(k), \quad x^p_j(k) = x^{2p-1}_j(k) + x^{2p}_j(k), \quad (6)$$

where $k = 1, 2, \ldots, 2^{J-p}$, $p = 1, 2, \ldots, J$ and $J = \log_2 N$.

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

$$X = \begin{bmatrix} x^1_1(k), x^2_1(k), \ldots, x^3_{32}(k) \end{bmatrix}. \quad (7)$$

### 2.3. Singular value decomposition

The MMG signal presentation matrix based on the WPT produces a large number 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 the 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

$$X = U \Sigma V^T,$$

where $U (M \times M)$ and $V (N \times N)$ are orthonormal matrices and $\Sigma$ is an $M \times N$ diagonal matrix of the 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 the 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 information about the muscle fiber vibration during different contraction patterns, but also 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 the 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 $\omega_1, \omega_2, \ldots, \omega_c$ is

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

where $q^{(i,k)}$ is the $k$th feature of $\omega_i$ and $N_i$ is the number of features in $\omega_i$.

The average distance of all features in $\omega_i$ can be determined as follows:

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

(9)

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

$$D_a = \frac{1}{c} \sum_{i=1}^{c} D_i.$$

(10)

Substituting equation (9) into equation (10) yields

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

(11)

where

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

(12)

is the mean of all features in $\omega_i$.

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

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

(13)
where
\[ \rho = \frac{1}{c} \sum_{i=1}^{c} \frac{1}{N_i} \sum_{k=1}^{N_i} q^{(i,k)} \] (14)
is the mean of all the features in all \( c \) motion patterns.

When the average distance \( D_a \) inside a certain motion pattern is smaller and the average distance between different motion patterns is bigger, the average represents the optimal features well. The evaluation criterion for the optimal features is defined as
\[ F = \frac{D_b}{D_a} \] (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

The 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 a 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 a mother wavelet due to its power to minimize the test set classification error. The class-separability-based objective functions were 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 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 the SVD methods. The STFT, also known as the windowed Fourier transform or spectrogram, is a development that extends the 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 the elements of wavelet transforms and the 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 the wavelet, improves the time resolution of high frequency events and the frequency resolution of low frequency events, in comparison to the STFT, while maintaining the absolute phase of each frequency component in contrast with the continuous wavelet transform’s. The STFT and SWT have been 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 biosignal feature extraction (Assous et al 2006). Different from the WPT-based method, the matrix used for the 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 are shown in figure 3. The MMG training dataset for each duration of 5 s was divided into discrete 256-sample epochs and inputted to the proposed classifier. The segment at the end of each motion which was not long enough for 256 samples was omitted in order to improve the quality of the training data (Huang et al 2005).

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 resulted from the wavelet packet decomposition into level 5 (figure 4). The results of feature selection using the 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 a higher distance evaluation index $F$. In contrast, the SVs with a 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 methods, the numbers of SVs obtained from the STFT, SWT and ST decomposition were different and they were 10, 9 and 26, respectively. However, the $F$ value distributions of the SVs of the three methods (figures 6–8) were similar to that of the WPT–SVD method. Comparing them with figure 5, it could be seen that the $F$ values of several SVs of the WPT were higher than the maximum $F$ value of the SVs of the other three methods. This means that the feature extracted by the 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 the WPT held better class separability among the four methods.
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Figure 4. The SVs of a MMG signal time–frequency representation matrix obtained from the WPT for subject 3.

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

After the distance evaluation index $F$ of each SV was computed, the SVs were reassigned in the order from a larger to lower $F$ value. Then, different dimensional eigenvectors were constructed according to the following rule, i.e. the first eigenvector was constructed by the SV with maximum $F$ in each of the two channels, the second eigenvector was constructed by the SVs with maximum and second maximum $F$ in each of the two channels till the last one, composed of all the SVs of the 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 the eigenvector dimension upon the validation set classification accuracy is shown in figure 10. All methods share a similar law, i.e. showing fluctuated responses. The accuracy increased at small numbers of SVs and then reached the highest. A further increase in the number of SVs does decrease the accuracy of the classifiers.

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

Figure 7. Distance evaluation of the SVs obtained from the SWT for subject 3.
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
Figure 10. The effect of the number of SVs 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 the wavelet packet transform (WPT), short-time Fourier transform (STFT), stationary wavelet transform (SWT) and S transform (ST) methods.

The classification accuracy of the WPT, STFT, SWT, ST methods 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 methods. 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
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>
<thead>
<tr>
<th>Method</th>
<th>WPT–SVD</th>
<th>STFT–SVD</th>
<th>SWT–SVD</th>
<th>ST–SVD</th>
</tr>
</thead>
<tbody>
<tr>
<td>WPT–SVD</td>
<td>–</td>
<td>0.0001</td>
<td>0.0018</td>
<td>0.0384</td>
</tr>
<tr>
<td>STFT–SVD</td>
<td>0.0001</td>
<td>–</td>
<td>0.6619</td>
<td>0.0102</td>
</tr>
<tr>
<td>SWT–SVD</td>
<td>0.0018</td>
<td>0.6619</td>
<td>–</td>
<td>0.073</td>
</tr>
<tr>
<td>ST–SVD</td>
<td>0.0384</td>
<td>0.0102</td>
<td>0.073</td>
<td>–</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Processing delay (ms)</th>
<th>WPT</th>
<th>STFT</th>
<th>SWT</th>
<th>ST</th>
</tr>
</thead>
<tbody>
<tr>
<td>TF representation</td>
<td>41</td>
<td>2</td>
<td>195</td>
<td>128</td>
</tr>
<tr>
<td>SVD</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>LDA</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>44</td>
<td>5</td>
<td>198</td>
<td>131</td>
</tr>
</tbody>
</table>

accuracy as compared with the STFT ($p = 0.0001$), SWT ($p = 0.0018$) and ST ($p = 0.0384$) methods. Meanwhile, the results indicated a distinct trend toward the improvement in the progression of STFT→SWT→ST→WPT.

For 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) 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 a 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

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 the skeletal muscle during the fusion of twitches (Orizio et al 2003). The bandwidth of the MMG signal is normally considered between 3 Hz and 100 Hz (Orizio 1993), while higher cutoff frequencies are used by some researchers (Beck et al 2005, Shima et al 2007, Yoshitake et al 2002). It contains a low frequency component with bigger amplitude due to the 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 a 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 the MMG frequency domain parameters. In the present work, a wavelet packet transform was applied as the MMG feature extractor due to its non-stationarity (Alves and Chau 2008).

Previous works on the achievements of MMG-powered prosthesis were limited to a single DOF. The main contribution of the present work is to confirm the potential of the 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 the MMG signals.

To achieve the goal of multiple degrees of motion using MMG classification, we proposed a new approach to construct a 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 were employed to the wavelet packet coefficient matrix for feature extraction. After being processed by the SVD method, sometimes there are still high noises, irrelevant or redundant information in these 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 the 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 the STFT, SWT and ST combined with the 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 the WPT–SVD to others is that the 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 the 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 the ST is superior to the SWT and STFT, though not as good as the 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, the 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 partitioning the time–frequency plane; once specified, each cell has an identical aspect ratio (Englehart et al. 1999). These factors may cause a significant difference in the classification errors among the ST, SWT and 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 do 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, their computational burden is larger than both the WPT and STFT. On the other hand, though the time consumption of the 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 to analyzing the 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 biosignals (such as EMG) to improve the accuracy of the decisions made for prosthetic control. However, it needs 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 the 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 are classified as more accurate than the 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 the transient data is decreased than with the steady-state data. Therefore, steady-state data with a shorter segment length, such as 128 ms, are 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 the 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 the MMG signal for multifunction prosthetic control. There are many papers that have examined the force-related patterns of the 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 be further investigated in future studies with better-controlled contraction strengths. EMG has been widely used as an information source for a 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 methods, such as a neural network, fuzzy logic, support vector machine, should be compared with the 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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