Feature reduction and selection for EMG signal classification

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ABSTRACT

Feature extraction is a significant method to extract the useful information which is hidden in surface electromyography (EMG) signal and to remove the unwanted part and interferences. To be successful in classification of the EMG signal, selection of a feature vector ought to be carefully considered. However, numerous studies of the EMG signal classification have used a feature set that have contained a number of redundant features. In this study, most complete and up-to-date thirty-seven time domain and frequency domain features have been proposed to be studied their properties. The results, which were verified by scatter plot of features, statistical analysis and classifier, indicated that most time domain features are superfluity and redundancy. They can be grouped according to mathematical property and information into four main types: energy and complexity, frequency, prediction model, and time-dependence. On the other hand, all frequency domain features are calculated based on statistical parameters of EMG power spectral density. Its performance in class separability viewpoint is not suitable for EMG recognition system. Recommendation of features to avoid the usage of redundant features for classifier in EMG signal classification applications is also proposed in this study.

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1. Introduction

Electromyography (EMG) signals have been widely used and applied as a control signal in numerous man–machine interface applications and have also been deployed in many clinical and industrial applications (Pandey & Mishra, 2009; Rafiee, Rafiee, Yavari, & Schoen, 2011). Widespread potential applications for surface EMG signal classification and control have been reported in the last two decades; including multifunction prosthesis, electrical wheelchairs, virtual mouse and keyboard, and virtual worlds (Oskoei & Hu, 2007). To be successful in classification and recognition of the surface EMG signals, three main cascaded modules should be carefully considered that consist of data pre-processing, feature extraction, and classification methods, particularly selection of an optimal feature vector (Boostani & Moradi, 2003; Zardoshti-Kermani, Wheeler, Badie, & Hashemi, 1995; Zecca, Micera, Carrozza, & Dario, 2002).

Feature extraction is a method to extract the useful information that is hidden in surface EMG signal and remove the unwanted EMG parts and interferences (Boostani & Moradi, 2003; Zardoshti-Kermani et al., 1995). Some features are robust across different kinds of noises; consequently, intensive data pre-processing methods shall be avoided to be implemented (Phinyomark, Limsakul, & Phukpattaranont, 2009a). In addition, appropriate features

will directly approach high classification accuracy (Oskoei & Hu, 2008). Three properties have been suggested to be used in quantitative comparison of their capabilities that include maximum class separability, robustness, and complexity (Boostani & Moradi, 2003; Zardoshti-Kermani et al., 1995). Although many research works have mainly tried to explore and examine an appropriate feature vector for numerous specific EMG signal classification applications (e.g. Boostani & Moradi, 2003; Oskoei & Hu, 2008; Phinyomark et al., 2009a; Zardoshti-Kermani et al., 1995; Zecca et al., 2002), there have a few works which make deeply quantitative comparisons of their qualities, particularly in redundancy point of view. Moreover, most recent EMG signal classification studies have still employed set of feature vectors that carried a number of redundant features (e.g. Du, Lin, Shyu, & Tainsong, 2010; Farfán, Politti, & Felice, 2010; Khezri & Jahed, 2009; Khushaba, Al-Ani, & Al-Jumaily, 2010; Kim, Choi, Moon, & Mun, 2011; Li, Li, Yu, & Geng, 2011; Li, Schultz, & Kuiken, 2010; Tenore et al., 2009).

The aims of this study are: to evaluate properties of the EMG features in space through observation of scatter plots and mathematical definitions for avoiding usage of redundant features in a classifier, and to examine a good feature vector using statistical analysis and classifier. Results of this study can be widely used and applied in many EMG signal classification studies, including medical and engineering applications, in order to keep away from using the redundant features in classification stage. For this purpose, complete and up-to-date thirty-seven time domain and frequency domain features have been evaluated in this study.

2. EMG feature extraction

Generally, features in analysis of the EMG signal can be divided into three main groups. There are time domain, frequency domain, and time-frequency or time-scale representation (Oskoei & Hu, 2007; Zecca et al., 2002). In this study, only first two feature groups, which are defined in time domain and frequency domain, have been considered because features in the last group, time-frequency/time-scale features, cannot be directly used by themself (Englehart, Hudgin, & Parker, 2001). Feature extracted from time-frequency/time-scale methods should be reduced their high dimensions before sending them to a classifier. Additionally, mathematical functions which were defined in time domain and frequency domain have been usually used as dimensionality reduction methods for time-frequency/time-scale domain features (Boostani & Moradi, 2003). Hence, study of feature extraction properties of time domain and frequency domain has recently become an important issue in the EMG signal classification. There are thirty-seven features that were used in this evaluation study. Most of them are defined in time domain. Small number features are computed in frequency domain. The mathematical definitions and the related works of these EMG features are listed below:

2.1. Time domain features

Features in time domain are usually quick and easy implemented, because these features do not need any transformation, which calculate based on raw EMG time series (Hudgins, Parker, & Scott, 1993; Oskoei & Hu, 2008; Tkach, Huang, & Kuiken, 2010). Time domain features have been widely used in both medical and engineering researches and practices. A major disadvantage of features in this group comes from a non-stationary property of the EMG signal, changing in statistical properties over time, but time domain features assume the data as a stationary signal (Lei, Wang, & Feng, 2001). Hence, variation of features in this group may be largely obtained when the surface EMG signal is recorded through dynamic movements. Moreover, due to their calculations based on EMG signal amplitude values, much interference that is acquired through the recording come to be a major disadvantage, particularly for features that are extracted from energy property (Phinyomark, Limsakul, & Phukpattaranont, 2009b). However, features in this group have also been widely used due to their classification performances in low noise environments and their lower computational complexity compared with features in frequency domain and time-scale domain. Twenty-six time domain features have been proposed in this study through extensively and carefully review the literatures.

2.1.1. Integrated EMG

Integrated EMG (IEMG) is normally used as an onset detection index in EMG non-pattern recognition and in clinical application (e.g. Huang & Chen, 1999; Merletti, 1996). It is related to the EMG signal sequence firing point. Definition of IEMG feature is defined as a summation of absolute values of the EMG signal amplitude, which can be expressed as

$$\text{IEMG} = \sum_{i=1}^{N} |x_i|, \tag{1}$$

where x_i represents the EMG signal in a segment i and N denotes length of the EMG signal.

2.1.2. Mean absolute value

Mean absolute value (MAV) is one of the most popular used in EMG signal analysis (e.g. Hudgins et al., 1993; Zardoshti-Kermani et al., 1995). It is similar to IEMG feature which is used as an onset

index, especially in detection of the surface EMG signal for the prosthetic limb control. However, there are many given names for calling this feature; for instance, average rectified value (ARV), averaged absolute value (AAV), integral of absolute value (IAV), and the first order of v-Order features (V1). MAV feature is an average of absolute value of the EMG signal amplitude in a segment, which can be defined as

$$\text{MAV} = \frac{1}{N} \sum_{i=1}^{N} |x_i|. \tag{2}$$

2.1.3. Modified mean absolute value type 1

Modified mean absolute value type 1 (MAV1) is an extension of MAV feature (e.g. Oskoei & Hu, 2008; Phinyomark et al., 2009a). The weighted window function w_i is assigned into the equation for improving robustness of MAV feature. It is calculated by

$$\text{MAV1} = \frac{1}{N} \sum_{i=1}^{N} w_i |x_i|; \tag{3}$$

$$w_i = \begin{cases} 1, & \text{if} \quad 0.25N \leqslant i \leqslant 0.75N \\ 0.5, & \text{otherwise} \end{cases}$$

2.1.4. Modified mean absolute value type 2

Modified mean absolute value type 2 (MAV2) is an expansion of MAV feature which is similar to the MAV1 (e.g. Oskoei & Hu, 2008; Phinyomark et al., 2009a). However, the weighted window function w_i that is assigned into the equation is a continuous function. It improves smoothness of the weighted function. The equation is defined as

$$\text{MAV2} = \frac{1}{N} \sum_{i=1}^{N} w_i |x_i|; \tag{4}$$

$$w_i = \begin{cases} 1, & \text{if} \quad 0.25N \leqslant i \leqslant 0.75N \\ 4i/N, & \text{elseif} \quad i < 0.25N \\ 4(i-N)/N, & \text{otherwise} \end{cases}$$

2.1.5. Simple square integral

Simple square integral (SSI) or integral square uses energy of the EMG signal as a feature (e.g. Du & Vuskovic, 2004). It is a summation of square values of the EMG signal amplitude. Generally, this parameter is defined as an energy index, which can be expressed as

$$\text{SSI} = \sum_{i=1}^{N} x_i^2. \tag{5}$$

2.1.6. Variance of EMG

Variance of EMG (VAR) is another power index (e.g. Park & Lee, 1998; Zardoshti-Kermani et al., 1995). Generally, variance is defined as an average of square values of the deviation of that variable; however, mean value of EMG signal is close to zero ($\sim 10^{-10}$). Hence, variance of the EMG signal can also be defined as

$$\text{VAR} = \frac{1}{N-1} \sum_{i=1}^{N} x_i^2. \tag{6}$$

2.1.7. Absolute value of the 3rd, 4th, and 5th temporal moment

Temporal moment is a statistical analysis that was proposed in study of Saridis and Gootee (1982) to be used in control of a prosthetic arm. Normally, the absolute value was taken to greatly reduce the within class separation for the odd moment case. The first moment and the second moment are similar to the MAV

and VAR features, respectively. In study of Saridis and Gootee (1982), the third, fourth, and fifth moments (TM3, TM4, and TM5) were used and also evaluated in this study. The definition of their equations can be respectively expressed as

$$TM3 = \left| \frac{1}{N} \sum_{i=1}^{N} x_i^3 \right|; \tag{7}$$

$$TM4 = \frac{1}{N} \sum_{i=1}^{N} x_i^4; \tag{8}$$

$$TM5 = \left| \frac{1}{N} \sum_{i=1}^{N} x_i^5 \right|. \tag{9}$$

2.1.8. Root mean square

Root mean square (RMS) is another popular feature in analysis of the EMG signal (e.g. Boostani & Moradi, 2003; Kim et al., 2011). It is modeled as amplitude modulated Gaussian random process whose relates to constant force and non-fatiguing contraction. It is also similar to standard deviation method. The mathematical definition of RMS feature can be expressed as

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2}. \tag{10}$$

2.1.9. v-Order

The v-Order (V) is a non-linear detector that implicitly estimates muscle contraction force m_i. It is defined from a functional mathematical model of the EMG signal generation (e.g. Tkach et al., 2010; Zardoshti-Kermani et al., 1995). It is given by the following expression

$$x_i = (\gamma m_i^\alpha) n_i, \tag{11}$$

where γ and α are constants, and n_i is class of the ergodic Gaussian processes. Although, α is theoretically 0.5, but from the experimental result obtained from study of Hogan and Mann (1980), it showed that α ranged between 1 and 1.75. An optimal value for v has been reported to be 2 (e.g. Tkach et al., 2010; Zardoshti-Kermani et al., 1995), which leads to the definition of RMS feature. A number of previous studies is also used the value of v as 2 that is defined in this study. The mathematical definition of the V feature is defined as

$$V = \left(\frac{1}{N} \sum_{i=1}^{N} x_i^v \right)^{\frac{1}{v}}. \tag{12}$$

2.1.10. Log detector

Like the V feature, this feature also provides an estimate of the muscle contraction force (e.g. Tkach et al., 2010; Zardoshti-Kermani et al., 1995). However, definition of the non-linear detector is changed to be based on logarithm and log detector (LOG) feature, which can be defined as

$$LOG = e^{\frac{1}{N} \sum_{i=1}^{N} \log(|x_i|)}. \tag{13}$$

2.1.11. Waveform length

Waveform length (WL) is a measure of complexity of the EMG signal (e.g. Hudgins et al., 1993; Oskoei & Hu, 2008). It is defined as cumulative length of the EMG waveform over the time segment. Some literatures called this feature as wavelength (WAVE). It can be calculated by

$$WL = \sum_{i=1}^{N-1} |x_{i+1} - x_i|. \tag{14}$$

2.1.12. Average amplitude change

Average amplitude change (AAC) is nearly equivalent to WL feature, except that wavelength is averaged (Fougner, 2007). It can be formulated as

$$AAC = \frac{1}{N} \sum_{i=1}^{N-1} |x_{i+1} - x_i|. \tag{15}$$

A number of research studies called this feature as difference absolute mean value (DAMV) (Kim et al., 2011); however, its definition divides WL value by length N minus one.

2.1.13. Difference absolute standard deviation value

Difference absolute standard deviation value (DASDV) is look like RMS feature, in other words, it is a standard deviation value of the wavelength (Kim et al., 2011), as can be defined by

$$DASDV = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (x_{i+1} - x_i)^2}. \tag{16}$$

2.1.14. Amplitude of the first burst

Amplitude of the first burst (AFB) is defined as the first maximum point which is extracted from resulting time function. It was established from the Robotics and NN laboratory (Du, 2003). Firstly, the raw EMG signal is squared and passed through a moving average FIR filter with Hamming windowing function. Secondly, after filtering the low frequency components of the EMG signal are obtained and the maximum value of the first burst is used as a feature. In this study, the window size of 32 ms was used for Hamming windowing function.

2.1.15. Zero crossing

Zero crossing (ZC) is a measure of frequency information of the EMG signal that is defined in time domain (e.g. Hudgins et al., 1993; Philipson, 1987). It is a number of times that amplitude values of the EMG signal cross zero amplitude level. To avoid low-voltage fluctuations or background noises, threshold condition is implemented and the calculation is defined as

$$ZC = \sum_{i=1}^{N-1} [\text{sgn}(x_i \times x_{i+1}) \cap |x_i - x_{i+1}| \geqslant \text{threshold}]; \tag{17}$$

$$\text{sgn}(x) = \begin{cases} 1, & \text{if } x \geqslant \text{threshold} \\ 0, & \text{otherwise} \end{cases}$$

2.1.16. Myopulse percentage rate

Myopulse percentage rate (MYOP) is an average value of myopulse output which is defined as one when absolute value of the EMG signal exceeds a pre-defined threshold value (e.g. Fougner, 2007; Philipson, 1987). Mathematically, it is calculated as

$$MYOP = \frac{1}{N} \sum_{i=1}^{N} [f(x_i)]; \tag{18}$$

$$f(x) = \begin{cases} 1, & \text{if } x \geqslant \text{threshold} \\ 0, & \text{otherwise}. \end{cases}$$

2.1.17. Willison amplitude

Willison amplitude or Wilson amplitude (WAMP) is a measure of frequency information of the EMG signal as same as defines in ZC feature (e.g. Philipson, 1987; Zardoshti-Kermani et al., 1995). It is a number of times resulting from difference between the EMG signal amplitude among two adjoining segments that exceeds a pre-defined threshold. Moreover, it is related to the firing of

motor unit action potentials (MUAP) and muscle contraction force. The definition is as

$$WAMP = \sum_{i=1}^{N-1}[f(|x_n - x_{n+1}|)];$$ (19)

$$f(x) = \begin{cases} 1, & \text{if } x \geqslant \text{threshold} \\ 0, & \text{otherwise}. \end{cases}$$

2.1.18. Slope sign change

Slope sign change (SSC) is related to ZC, MYOP, and WAMP features (e.g. Hudgins et al., 1993; Philipson, 1987). It is another method to represent frequency information of the EMG signal. It is a number of times that slope of the EMG signal changes sign. The number of changes between the positive and negative slopes among three sequential segments is performed with the threshold function for avoiding background noise in the EMG signal. This can be mathematically expressed as

$$SSC = \sum_{i=2}^{N-1}[f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]];$$ (20)

$$f(x) = \begin{cases} 1, & \text{if } x \geqslant \text{threshold} \\ 0, & \text{otherwise}. \end{cases}$$

The suitable value of threshold parameter of the ZC, MYOP, WAMP, and SSC features is normally chosen between 50 μV and 100 mV (e.g. Boostani & Moradi, 2003; Phinyomark et al., 2009a,2009b; Zardoshti-Kermani et al., 1995). It is dependent on setting of gain value of the instrument and on level of background noises.

All twenty features mentioned above (Eqs. (1)–(20)) provide only one feature per muscle channel, which is small enough to combine with other features for making a more powerful feature vector. However, from observation of the mathematical functions, it may have the same discrimination in space which makes a redundancy. To increase valuable of time domain features, increasing number of segments may improve feature representation of the original EMG signal (Du, 2003). While feature vector's discrimination performance has been increased, increasing features will increase computational burden for a classifier. Hence, to provide this method to be valuable, number of features has to be kept to a minimum as possible as maximum in class separability has been approached. Moreover, two prediction models have also been proposed to increase the number of features in time domain. The remainders, six time features, are proposed as follows:

2.1.19. Mean absolute value slope

Mean absolute value slope (MAVSLP) is a modified version of MAV feature to establish multiple features (e.g. Miller, 2008; Zecca et al., 2002). Differences between MAVs of the adjacent segments are determined. The equation can be defined as

$$MAVSLP_k = MAV_{k+1} - MAV_k; \quad k = 1, \ldots, K-1$$ (21)

where K is number of segments covering the EMG signal. When number of segments increases, it may improve representation of the original EMG signal over traditional MAV feature. In study of Miller (2008), number of segments K is set to 3 that is also used in this study.

2.1.20. Multiple hamming windows

Multiple hamming windows (MHW) are an original version of multiple time windows method (e.g. Du & Vuskovic, 2004). An idea of the multiple time windows method is to capture the change of EMG signal's energy with respect to time by various multiple windowing functions. The raw EMG signal is segmented by the

Hamming windows on all time series. The MHW features are computed using each window's energy, which can be expressed as

$$MHW_k = \sum_{i=0}^{N-1}(x_i w_{i-i_k})^2, \quad k = 1, \ldots, K$$ (22)

where w is the Hamming windowing function. In study of Du (2003), three segments were recommended to be used with 30% overlap.

2.1.21. Multiple trapezoidal windows

Multiple trapezoidal windows (MTW) are one type of the multiple time windows method (e.g. Du & Vuskovic, 2004). Like the MHW, this feature method uses the energy contained inside a window as feature values, but the function of window w is changing from the Hamming windows to the trapezoidal windows, which in Du's study, the trapezoidal windowing function performed the best ones. It is defined as

$$MTW_k = \sum_{i=0}^{N-1}(x_i^2 w_{i-i_k}), \quad k = 1, \ldots, K.$$ (23)

The number of windows K is set to 3 for MTW as same as defined in MHW but the overlap windows is set to 30% (Du, 2003).

2.1.22. Histogram of EMG

Histogram of EMG (HIST) is an extension version of the ZC and WAMP features (e.g. Boostani & Moradi, 2003; Zardoshti-Kermani et al., 1995); therefore, this feature also provides frequency information. However, ZC and WAMP features applied a single threshold for the EMG signal, but HIST feature divides elements in the EMG signal into B equally spaced segments and returns number of signal elements for each segment. Zardoshti et al. (2002) recommended number of levels B as 9.

2.1.23. Auto-regressive coefficients

Auto-regressive (AR) model is a prediction model that describes each sample of the EMG signal as a linear combination of the previous samples x_{i-p} plus a white noise error term w_i (e.g. Boostani & Moradi, 2003; Park & Lee, 1998; Zardoshti-Kermani et al., 1995). In classification of the EMG signal, coefficients of the AR model a_p have been used as a feature vector. The model is basically expressed as the following form:

$$x_i = \sum_{p=1}^{P}a_p x_{i-p} + w_i,$$ (24)

where P is the order of the AR model. The forth-order AR was suggested from many previous research works (e.g. Paiss & Inbar, 1987).

2.1.24. Cepstral coefficients

Cepstral or Cepstrum analysis is defined as the inverse Fourier transform of the logarithm of power spectrum magnitude of the signal data (e.g. Park & Lee, 1998; Zecca et al., 2002). Coefficients of the Cepstral analysis (CC) have been used as a feature as same as the AR model and its coefficients can be derived from the AR model (e.g. Tkach et al., 2010; Zecca et al., 2002), which were computed as

$$c_1 = -a_1;$$

$$c_p = -a_p - \sum_{l=1}^{p-1}\left(1 - \frac{l}{p}\right)a_P c_{p-l},$$ (25)

where c_p is the pth order coefficients of the Cepstral analysis and $1 \leqslant l \leqslant P$. From the provided definition, this feature can be considered as a time domain feature because it does not require a Fourier transform in process. From the suggestion of the suitable AR order, in this study the forth order CC was also implemented.

2.2. Frequency domain features

Frequency or spectral domain features are mostly used to study fatigue of the muscle and MU recruitment analysis. Power spectral density (PSD) becomes a major analysis in frequency domain. Different kinds of statistical properties were applied to the PSD which is defined as a Furrier transform of the autocorrelation function of the EMG signal. It can be estimated using either Periodogram or parametric methods, i.e., the AR model (Farina & Merletti, 2000). Two widely used variables of the PSD are mean frequency and median frequency (MNF and MDF). There are other characteristic variables, e.g., peak frequency (PKF), mean power (MNP), and total power (TTP). Eleven frequency domain features are defined and their definitions are described as follows:

2.2.1. Mean frequency

MNF is an average frequency which is calculated as sum of product of the EMG power spectrum and the frequency divided by total sum of the spectrum intensity (e.g. Oskoei & Hu, 2008). Central frequency (f_c) and spectral center of gravity are other calling names of MNF feature (Du & Vuskovic, 2004). It can be calculated as

$$\text{MNF} = \sum_{j=1}^{M} f_j P_j \bigg/ \sum_{j=1}^{M} P_j, \tag{26}$$

where f_j is frequency of the spectrum at frequency bin j, P_j is the EMG power spectrum at frequency bin j, and M is length of the frequency bin.

2.2.2. Median frequency

MDF is a frequency at which the spectrum is divided into two regions with equal amplitude, in other words, MDF is half of TTP feature (e.g. Oskoei & Hu, 2008). It can be expressed as

$$\sum_{j=1}^{\text{MDF}} P_j = \sum_{j=\text{MDF}}^{M} P_j = \frac{1}{2} \sum_{j=1}^{M} P_j. \tag{27}$$

2.2.3. Peak frequency

PKF is a frequency at which the maximum power occurs (e.g. Biopac Systems, 2010). It is given by

$$\text{PKF} = \max(P_j), \quad j = 1, \ldots, M. \tag{28}$$

2.2.4. Mean power

MNP is an average power of the EMG power spectrum (e.g. Biopac Systems, 2010). The calculation is defined as

$$\text{MNP} = \sum_{j=1}^{M} P_j \bigg/ M. \tag{29}$$

2.2.5. Total power

TTP is defined as an aggregate of the EMG power spectrum (e.g. Biopac Systems, 2010). Zero spectral moment (SM0) and energy are other generally names (Du & Vuskovic, 2004). The definition is as

$$\text{TTP} = \sum_{j=1}^{M} P_j = SM0. \tag{30}$$

2.2.6. The 1st, 2nd, and 3rd Spectral moments

Spectral moment is an alternative statistical analysis way to extract features from the EMG power spectrum. The first three moments (SM1–SM2) are the most important spectral moments (Du

& Vuskovic, 2004). The definition of their equations can be expressed as

$$\text{SM1} = \sum_{j=1}^{M} P_j f_j; \tag{31}$$

$$\text{SM2} = \sum_{j=1}^{M} P_j f_j^2; \tag{32}$$

$$\text{SM3} = \sum_{j=1}^{M} P_j f_j^3. \tag{33}$$

2.2.7. Frequency ratio

Frequency ratio (FR) is proposed to distinguish between contraction and relaxation of muscle using ratio between the low frequency components and the high frequency components of the EMG signal (e.g. Han et al., 2000; Oskoei & Hu, 2006, 2008). The equation is defined as

$$\text{FR} = \sum_{j=\text{LLC}}^{\text{ULC}} P_j \bigg/ \sum_{j=\text{LHC}}^{\text{UHC}} P_j, \tag{34}$$

where ULC and LLC are the upper- and lower-cutoff frequency of the low frequency band and UHC and LHC are the upper- and lower-cutoff frequency of the high frequency band, respectively. The threshold for dividing between low frequencies and high frequencies can be defined by two ways. First way, the frequency bands are decided through the experiments. For instance, Han et al. (2000) used 30–250 Hz for low frequency component and 250–1000 Hz for high frequency component. Second way, the high and the low frequency bands are defined by using a value of MNF feature (Oskoei & Hu, 2006). From mathematical definition, FR feature is an inverse case of high-to-low ratio (H/L ratio) feature, which is widely used in study of diaphragmatic fatigue (Gross, Grassino, Ross, & Macklem, 1979).

2.2.8. Power spectrum ratio

Power spectrum ratio (PSR) can be seen as an extension version of PKF and FR features (Qingju & Zhizeng, 2006). The PSR is defined as ratio between the energy P_0 which is nearby the maximum value of the EMG power spectrum and the energy P which is the whole energy of the EMG power spectrum. Its calculation can be written by

$$\text{PSR} = \frac{P_0}{P} = \sum_{j=f_0-n}^{f_0+n} P_j \bigg/ \sum_{j=-\infty}^{\infty} P_j, \tag{35}$$

where f_0 is a feature value of the PKF and n is the integral limit. In this study, n is set to 20 and the energy of P is set to 10 and 500 Hz due to main energy of the EMG signal (Qingju & Zhizeng, 2006).

2.2.9. Variance of central frequency

Variance of central frequency (VCF) is one of an important characteristic of the PSD (Du & Vuskovic, 2004). It can be defined by using few spectral moments. It can be written as

$$\text{VCF} = \frac{1}{SM0} \sum_{j=1}^{M} P_j (f_j - f_c)^2 = \frac{\text{SM2}}{\text{SM0}} - \left(\frac{\text{SM1}}{\text{SM0}}\right)^2. \tag{36}$$

3. Materials and methods

3.1. EMG data acquisitions

3.1.1. Dataset 1: Evaluating redundancy of EMG features

The EMG data that were used for the first aim of this study were recorded from two useful forearm muscle channels, namely flexor

carpi radialis muscle (CH.A) and extensor carpi radialis longus muscle (CH.B), as shown in Fig. 1. A healthy male volunteer was asked to perform six daily-life upper-limb movements, including hand open (HO), hand close (HC), wrist extension (WE), wrist flexion (WF), forearm pronation (FP) and forearm supination (FS), as shown in Fig. 2. In experiment, a subject performed each movement at constant force contraction for a second and switched between relaxation (4 s interval) and static contraction, and then repeated the patterns for 10 times. After recording, 10 data sets for each movement were stored for the processing stage. Sample length of the EMG data is set to 256 ms during beginning of the movement because this span contains information of movement data (Graupe & Cline, 1975), and the response time for the prosthetic limb control should be less than 300 ms in order to reach the real-time constraint (Englehart et al., 2001). Surface electrodes (3M red dot 2.5 cm. foam solid gel) and a 16 bits A/D converter board (NI, USA, IN BNC-2110) were used. Two pairs of the surface electrodes were deployed with 2 cm inter-electrode distance. A band-pass filter of 10–500 Hz bandwidth and an amplifier with 60 dB gain were used. Sampling frequency was set at 1000 Hz.

3.1.2. Dataset 2: Searching optimal representative EMG features

The EMG data that have been proposed for the second aim were collected from twenty normal young subjects (10 males and 10 females). The EMG data were collected from five positions on the right arm using bipolar Ag/AgCl electrodes (H124SG, Kendal ARBO). The five muscle positions were: extensor carpi radialis longus muscle (CH.1), extensor carpi ulnaris muscle (CH.2), extensor digitorum communis muscle (CH.3), flexor carpi radialis muscle (CH.4), and biceps brachii muscle (CH.5), as shown in Fig. 1. The EMG signals were amplified and sampled by a commercial wireless EMG measurement system (Mobi6-6b, TMS International B.V.). A band-pass filter of 20–500 Hz bandwidth and an amplifier with $19.5\times$ gain were used. Sampling frequency was set at 1024 Hz. The EMG data were collected as the volunteers performed six upper-limb movements same as the first EMG data set (HO, HC, WE, WF, FP, and FS). Within each trial, the subject maintained each movement for two seconds in duration and separated each movement by a two-second period rest state (R) to avoid a transitional stage (i.e. during movement changes). Moreover, thirteen-second rest periods were also introduced at the beginning and the end of each trial to give a preparation time for the subject and to avoid any incomplete data recording that could be cut off before an action is finished. Each day, each subject completed three sessions, with five trials in each session. The order of movements was randomized in each session. Moreover, to study the fluctuation of the EMG signal, these three sessions per day were employed on
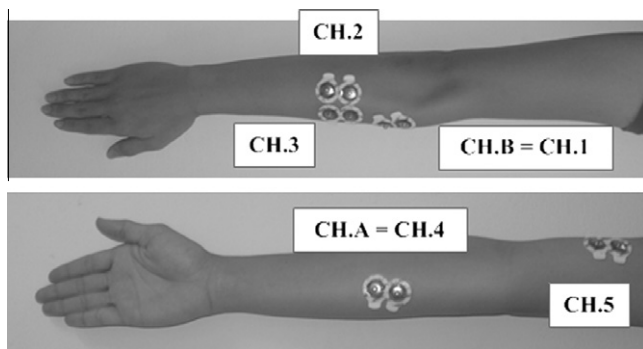

Fig. 1. The electrode positions of 2 (CH.A and CH.B) and 5 (CH.1–CH.5) channels that were placed on the forearm and upper-arm. The grounding electrode is on the wrist.
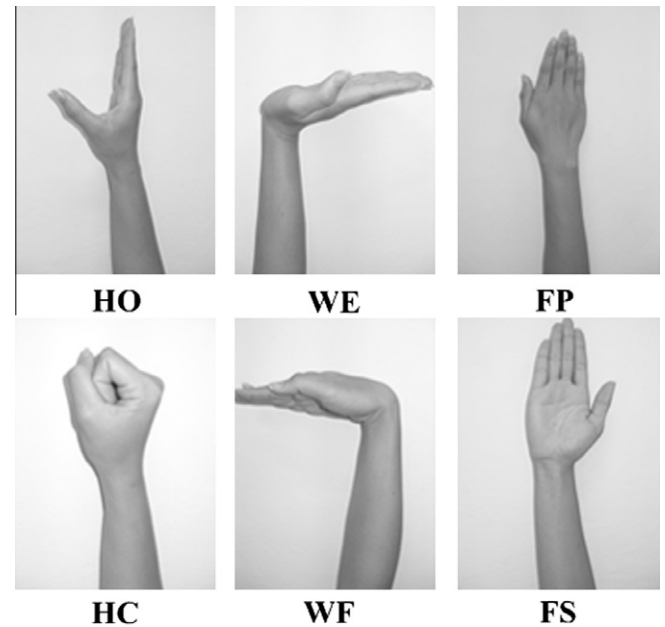

Fig. 2. Six upper-limb movements.

four separate days. In total, 60 datasets with duration of two seconds were collected for each movement from each subject. However, to render easier processing all rest states were removed before an extraction step was performed.

3.2. Evaluation methods

3.2.1. Dataset 1: Scatter plot

To study redundancy of EMG features, scatter plot has been used to evaluate discriminating patterns of features in space. A scatter plot is one of the useful mathematical diagrams that display values of two variables of a data set using Cartesian coordinates. Two variables can be defined from one feature per channel with two muscle channels or from two features with only a muscle channel. To be easily observed using scatter plot, the EMG signals from two efficient forearm muscle positions were used with six daily-life upper-limb movements. A small data set obtained from only a healthy subject and ten trials per movement was used in the evaluation, whereas, throughout the study, we confirmed that this simple data set offered a similar trend result with large data sets obtained from twenty subjects, which were used in the experiments of part 2 of this study. The description of the EMG data will be explained in next section. So as to easily observe and demonstrate, min–max normalization method has been proposed, as can be shown as

$$normfeat_i = \frac{feat_i - \min_i}{\max_i - \min_i}, \tag{37}$$

where *feat* and *normfeat* are original and normalized feature values that the value of *normfeat* is range between 0 and 1. The $\min_i$ and $\max_i$ are the minimum and the maximum values of every features in each dimension i (each muscle channel). Through the experiments, features in time domain and frequency domain have been grouped into several types for avoiding usage of redundant features.

3.2.2. Dataset 2: Linear discriminant analysis classifier and other authors' feature sets

To find the representative and the optimal features in each group in class separability point of view and to show the redundant usages of the existing successful EMG feature vectors, a large

data set, obtained from 20 subjects, has been proposed to yield classification accuracy results. A simple and efficient linear discriminant analysis (LDA) classifier was applied in the study for classification of six movement classes. LDA classifier has been used due to the high performance in classification of the EMG signal, the robustness in a long-term effect usage, and low computational cost (Englehart et al., 2001; Kaufmann, Englehart, & Platzner, 2010). The results of the LDA were performed by a 10-fold cross validation in each subject and the classification accuracy was computed as an average accuracy based on the results from cross validation testing of all subjects. Best performance of feature is approached when the classification accuracy reaches its highest value.

Furthermore, to illustrate the usages of existing redundant feature sets and to introduce the solutions to search an appropriate feature set, a number of the existing combinations of time domain features will be discussed. We selected two successful EMG feature sets that are (1) Hudgins's feature set: MAV, WL, ZC, and SSC (Hudgins et al., 1993), and (2) Du's feature set: IEMG, VAR, WL ZC, SSC, and WAMP (Du et al., 2010).

4. Results and discussion

Example of the EMG signals acquired from five muscles with six upper-limb movements are illustrated in Fig. 3. From the figure, we can observe that amplitude shape of the EMG signals were significantly different according to the direction of that movement.

4.1. Evaluating redundancy of EMG features

The scatter plots of thirty-seven EMG features in time domain and frequency domain are shown in Figs. 4–6. Based on the obtained results in Figs. 4 and 5, all time domain features can be divided and grouped into four main types based on observation of the scatter plots and mathematical properties. There are energy and complexity information methods, frequency information method, prediction model method, and time-dependence method.

Features in the first group are calculated based on amplitude values of the EMG signal. Discriminating patterns of feature values in space of this group are most likely similar to each other that can be observed through Figs. 4(a) and (b). This group can split into two subclasses that are based on energy information and complexity information. Pattern movement orders of two subclasses have a little difference that we can observed between Fig. 4(a) and (b). Features that are based on energy information consist of nine features: IEMG, MAV, MAV1, MAV2, SSI, VAR, RMS, *V*, and LOG. An arrangement of the feature values from smallest to largest in movement sequence of CH.A are WE, HO, FS, FP, HC and WF, and CH.B are WF, HC, FP, FS, HO and WE. For complexity information features, they consist of three features: WL, AAC, and DASDV. Only

FS and HO movements for CH.A, and FP and HO movements for CH.B are swapped. In addition, TM3, TM4, and TM5 features can be merged into this group due to their mathematical definition (calculating based on the EMG amplitude values); whereas, a power of high value in the equation makes their feature values of each movement to be (close to) zero, as shown in Fig. 4(c). Usages of redundant features from this group have been frequently found to be used in classification of the EMG signals. In addition, all scatter plots of thirty-seven features are shown in the Supplementary data.

The second group, features contain frequency information by calculating features in time domain. There are ZC, MYOP, WAMP, and SSC. Through the experiments with the first EMG data, optimal threshold value is set to 50 for all features in this group. Most pattern orders of features in this group are similar to the pattern orders of features in the first group, which is based on energy information, as shown in Figs. 4(d) and (e). However, features contained from each movement of these groups have different values. In addition, AFB can be considered to be combined to this group based on its implementation that is dependent on window size of low-pass filter. Its classification performance has a few good, but its discriminative pattern has much difference compared to the others. Its scatter plot is shown in Fig. 4(f).

The third features group coefficients of prediction model have been used as a feature vector. When order of the model increased, number of features also increased. Features in this group are AR and CC that were implemented with the fourth order. Many research works found that features in this group is better than features in the first and the second groups, but most works used unfair comparison. That is a feature vector of the prediction model contained more than one element but a feature vector of the first or the second group contained only one element. In this study, each coefficient is separately observed its scatter. From mathematical definitions of the AR and the CC methods that can be converted using a simple equation, discriminative patterns of the AR and the CC features seem to be similar to each other for each movement, as we can observe in Figs. 5(a) and (b). The pattern order in this group is more different than the pattern order in the first and the second groups.

The fourth and the last group of features in time domain are developed from features in the first and the second groups by segmenting the raw EMG signals. The extension versions of features based on energy information consist of MAVS, MHW, and MTW features. Much difference in discriminative patterns of MAVS is obtained as shown in Figs. 5(c) and (d), but its class separability is poor. In other words, the scatters of feature values obtained from MHW and MTW methods are similar to the scatters of features acquired from the first time-domain group, as shown in Fig. 5(e), whereas their classification performance are poorer than the old ones. Another multiple feature is extended from the second time-domain-feature group that is HIST. For instance, scatter plot of the first coefficient of segment 9 is shown in Fig. 5(f) that the discrimination in space of feature is very bad.

After evaluation and discussion of redundancy of the features in time domain, features in frequency domain have also been discussed. All frequency domain features are calculated based on statistical parameters of the PSD. However, their performances in class separability viewpoint have been shown that they are not suitable for the EMG recognition system. Some frequency domain features have the same discrimination in feature space as features in time domain that consist of five features: MNP, TTP, SM1, SM2, and SM3. Their scatter plots are shown in Figs. 6(a) and (b). Next, MDF and MNF are two popular frequency features that have the same scatters as can be observed in Figs. 6(c) and (d). The MNF feature showed a better performance than the MDF feature. Another four frequency features, namely, PKF, VCF, FR, and PSR, have the
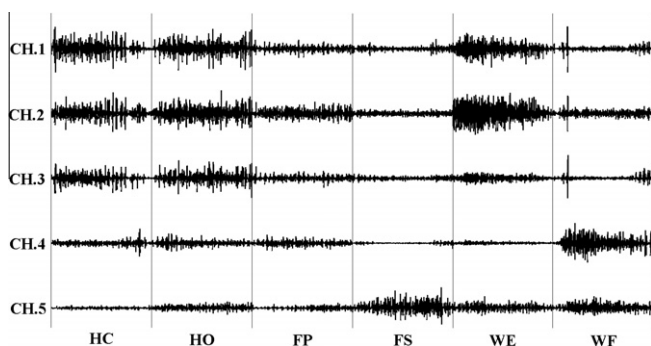

Fig. 3. Five-channel surface EMG signals according to six daily-life upper-limb movements in time domain.
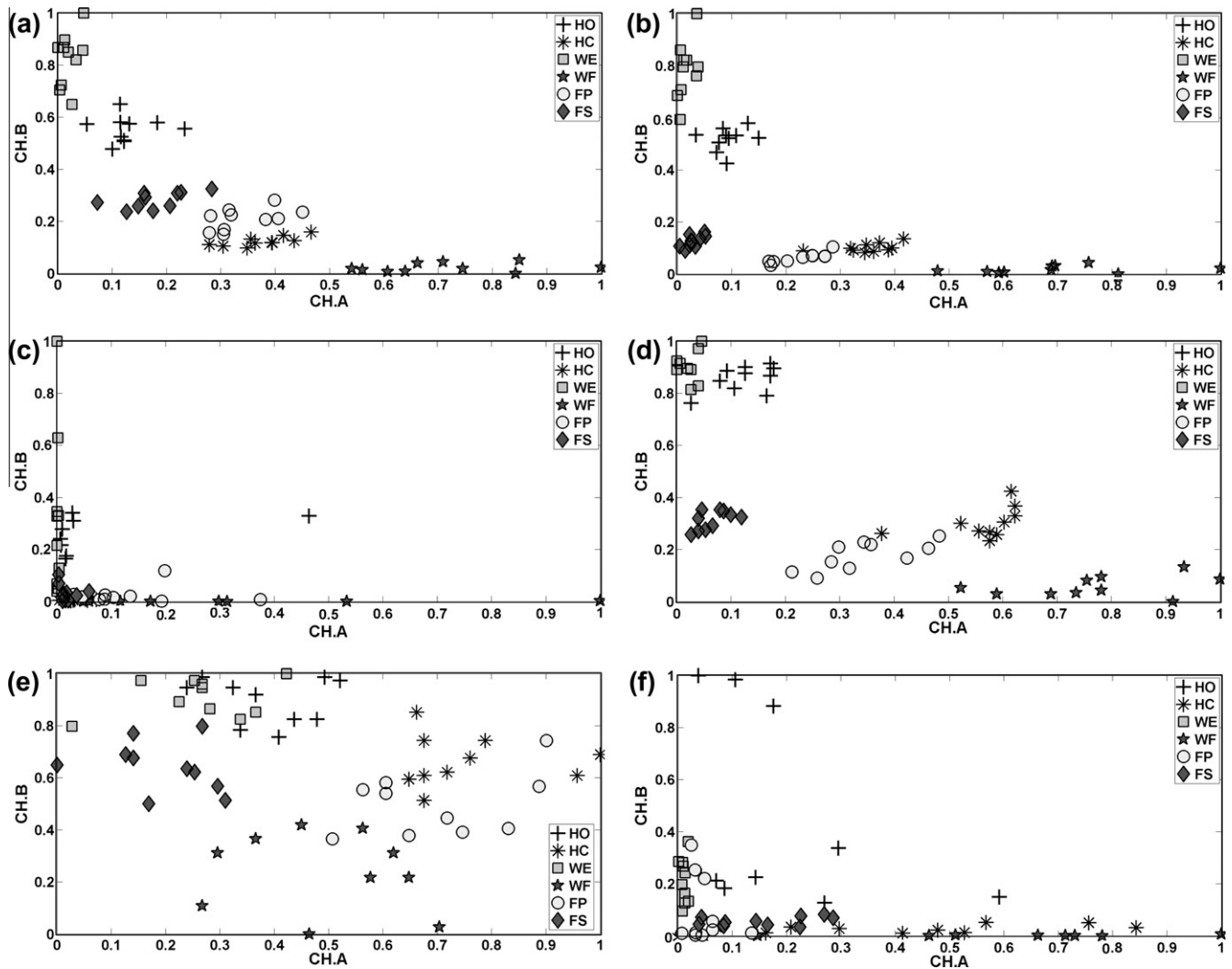
Fig. 4. Scatter plots of time domain features for 2 channels and 6 movements of a subject by applying: (a) MAV, (b) WL, (c) TM3, (d) WAMP, (e) SSC, and (f) AFB.

different patterns. PKF, VCF, and FR show very poor scatter while the scatter of PSR shows better ability for some specific low-level movements, i.e., FP and FS. The scatters of PKF and PSR are shown in Figs. 6(e) and (f).

4.2. Searching optimal representative EMG features

Based on the obtained classification accuracies in Table 1, optimal features in each group of time domain and frequency domain were examined. Firstly, four time-domain-feature groups have been discussed, including energy and complexity information features, frequency information features, prediction model features, and time-dependence features. For features in the first time-domain group, features based on complexity information, second subclass, are superior to features based on energy information, first subclass. MAV is recommended to be used as a representative feature in the first subclass and WL is recommended to be used as a representative feature in the second subclass. The performance of WL feature is similar to AAC and DASDV features but computational cost of WL is less than both features. The combination between features in the first and the second subclasses increases a little performance of class separability due to only small difference in feature space. The second group is features based on frequency information. From results of classification accuracies showed that classification performance of features in this group is equal; nevertheless, from our previous studies (Phinyomark et al., 2009b), robustness of WAMP

feature has been found. From our viewpoint, we recommended to use WAMP as a candidate feature for this group. The third group is the coefficients of the prediction model. Classification performance of AR features is slightly better than CC features. Due to observation in scatter graphs, poor ability in classification is shown. Scatter of the AR and CC features in space are worse than the scatter of the representative features in the first and the second groups, i.e. MAV, WL and WAMP, in space. However, use of all AR and CC coefficients of their orders is still significance due to their mathematical basis. For reasonable comparison, three features (three elements in feature vector) in the first and the second groups that consist of MAV, WL and WAMP are used to compare with the forth-order AR and CC, which consist of four elements in feature vector. Through experiments, classification accuracy of the combined MAV, WL and WAMP features is 94.2%, but classification accuracies of the AR and CC features are 92.1% and 91.5%, respectively. However, AR coefficient features have been still a useful augmenting feature for increasing the classification performance. For instance, we combined three mentioned features with the forth-order AR features that its classification result approach to 97%. The fourth and the last group of features in time domain are time-dependence methods. From the results of classification accuracies showed that classification performance of the extension versions of features based on energy information is not better than the original versions of that features. For extension version of features based on frequency information, namely HIST, its performance was found to be better than
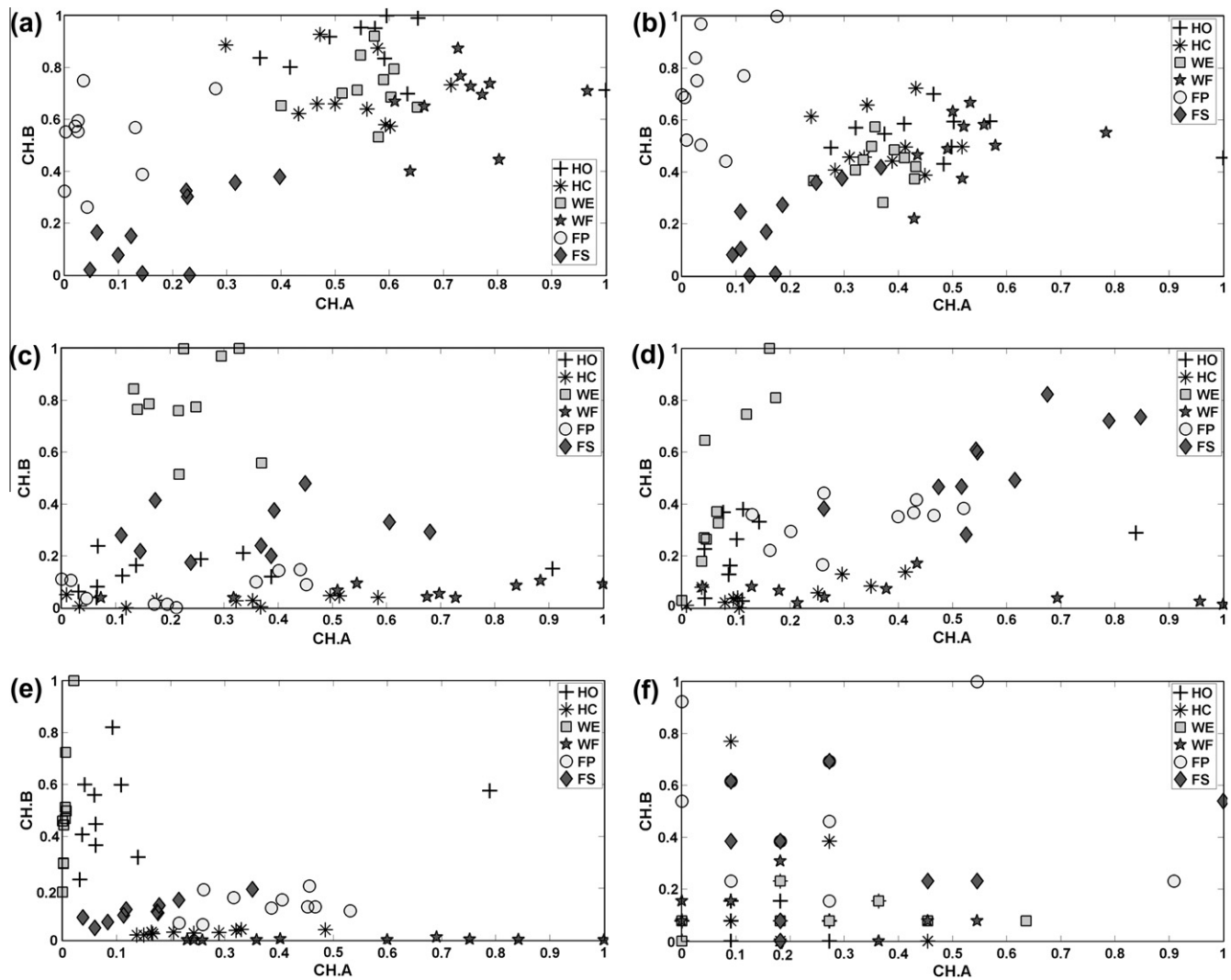
Fig. 5. Scatter plots of time domain features for 2 channels and 6 movements of a subject by applying: (a) AR (2nd coefficient), (b) CC (2nd coefficient), (c) MAVS (1st coefficient), (d) MAVS (2nd coefficient), (e) MTW (1st segment), and (f) HIST (1st segment).

other time domain features in a number of research works; however, that comparisons are unfair as same as founding in the AR and CC features evaluating studies. The discrimination in space of HIST features is very bad that is confirmed by their classification accuracies. Use of all HIST elements is still importance as same as mentioned for AR and CC methods; however, from out experiment, classification accuracy of all nine segments is still very poor that is 34.82%. From the large data employed in this study, we believe that the performance of HIST is not suitable for the EMG signal classification. Secondly, several frequency domain features including MNP, TTP, SM1, SM2 and SM3, have the same discrimination in feature space as features in time domain. Their classification accuracies are nearly found from the features in time domain, as presented in Table 1. Hence, time domain features are superior to features in frequency domain due to their low complexity. In addition, time domain features do not require any transformation.

The classification performance of each time domain and frequency domain features as well as some possible combinations of the features were estimated. The average accuracy of each feature from twenty subjects was shown in Table 1. It is employed to confirm the ability of all EMG features. To illustrate the usages of existing redundant feature sets and to introduce the solutions to search an appropriate feature set, Hudgins's feature set and Du's

feature set have been evaluated and discussed. Overall average and highest classification accuracies of combinations of features for both feature sets were respectively shown in Figs. 7 and 8. There were four one-feature sets, six two-feature sets, four three-feature sets and one four-feature set from combination cases of Hudgins's feature set, and there were six one-feature sets, fifteen two-feature sets, twenty three-feature sets, fifteen four-feature sets, six five-feature sets and one six-feature set from combination cases of Du's feature set.

Firstly, popularity of Hudgins's feature set has been established by many recent EMG classification studies (e.g. Li et al., 2010; Li et al., 2011). When the feature number increased from one to four, the average classification accuracy ranged from 87.61% to 95.67%. Classification accuracy was increasing in accordance with the feature number increasing; however, when number of features was greater than two, classification accuracy had a slight increase. It can be described from the investigation discussed above that MAV and WL have a little difference in discriminating pattern; in addition, ZC and SSC have a same distribution in space. Hence, the petty increase of classification accuracy has been definitely obtained, therefore using three features, i.e., MAV, WL and SSC, could achieve similar performance as using all features. This exploration is also discovered in other studies with different EMG data; for
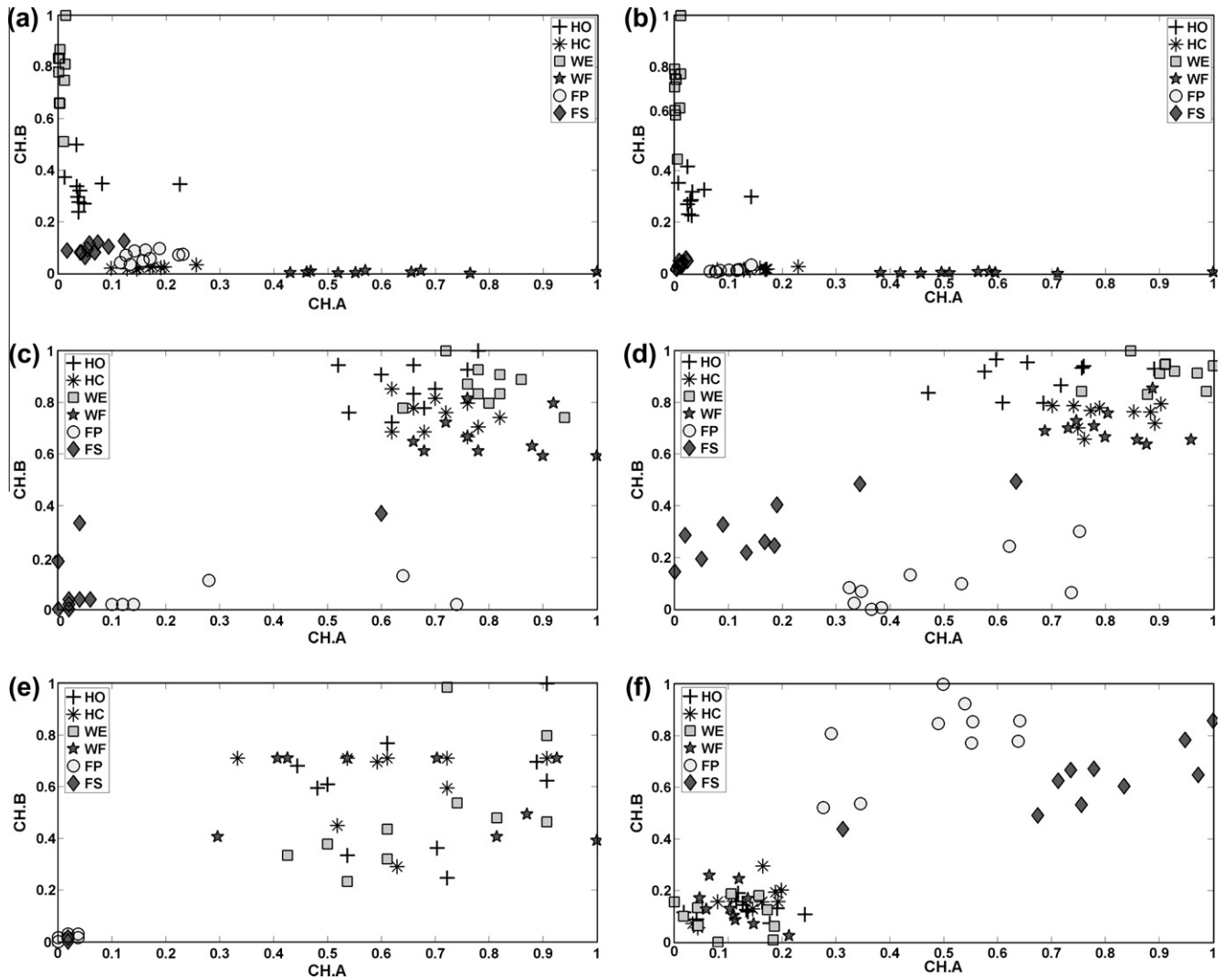
Fig. 6. Scatter plots of frequency domain features for 2 channels and 6 movements of a subject by applying: (a) MNP, (b) SM1, (c) MDF, (d) MNF, (e) PKF, and (f) PSR.

Table 1
Means and standard deviations (STD) of classification accuracy (%) obtained from all time domain and frequency domain features of dataset 2. N.B. Averaged classification accuracies of AR, CC, MAVS, MHW, MTW, and HIST features, when each single coefficient was individually used to classify per time are 71.28%, 75.09%, 55.40%, 73.13%, 75.00% and 24.92%, respectively.

Time domain								Frequency domain	
Group 1	Mean ± STD	Group 2	Mean ± STD	Group 3	Mean ± STD	Group 4	Mean ± STD	Feature	Mean ± STD
IEMG	86.74 ± 9.9	ZC	86.93 ± 8.1	AR	92.11 ± 6.3	MAVS	69.56 ± 11.2	MNP	78.31 ± 9.3
MAV	86.49 ± 9.6	MYOP	85.53 ± 10.0	CC	91.55 ± 6.8	MHW	78.33 ± 9.7	TTP	78.61 ± 9.1
MAV1	86.31 ± 9.8	WAMP	85.03 ± 9.7			MTW	81.88 ± 8.2	SM1	79.81 ± 9.1
MAV2	85.31 ± 9.9	SSC	88.31 ± 7.7			HIST	34.82 ± 4.9	SM2	80.29 ± 9.1
SSI	78.63 ± 9.1	AFB	71.64 ± 7.9					SM3	79.94 ± 8.8
VAR	78.42 ± 9.2							MDF	70.54 ± 10.4
RMS	86.21 ± 9.4							MNF	75.56 ± 11.8
V	86.21 ± 9.4							PKF	44.63 ± 7.2
LOG	83.32 ± 9.8							VCF	16.93 ± 2.6
WL	88.72 ± 7.2							FR	69.81 ± 8.9
AAC	88.42 ± 7.9							PSR	49.72 ± 8.9
DASDV	88.79 ± 7.3								
TM3	50.96 ± 7.6								
TM4	59.53 ± 7.3								
TM5	41.65 ± 5.1								

example, study of Liu et al. used EMG data obtained from transradial amputees with eleven wrist and hand movements (Liu, Zhou, Yang, & Li, 2009).

Secondly, in the same way as in the previous feature set, when the number of features was greater than two, the classification

accuracy had a slight increase for Du's feature set. IEMG and VAR have a same distribution in space, thus only best feature in this group is remained, and that is discovered with ZC, SSC and WAMP. From the experiments, IEMG and WAMP are recommended to be used as representative feature in that group. Moreover, addition
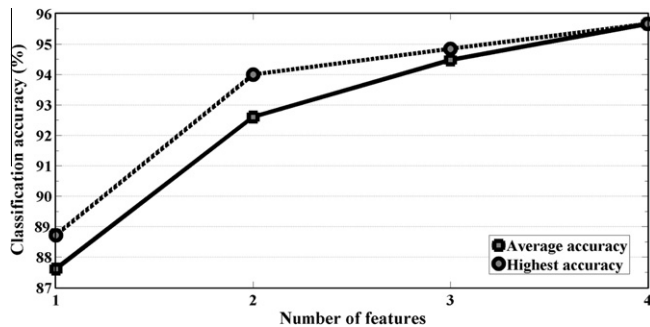
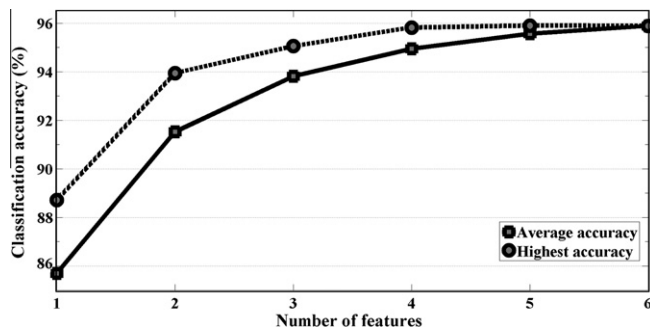**Fig. 7.** Overall average and highest classification accuracies for Hudgins's feature set.

Fig. 8. Overall average and highest classification accuracies for Du's feature set.

of WL increased a little classification rate due to tiny different distribution in space. In brief, the outcomes of this investigation may aid future development of the practical multifunction myoelectric control system. Usage of best feature in each time domain group could achieve similar performance as using more redundant features as can be employed for many recent studies (e.g. Farfán et al., 2010; Khezri & Jahed, 2009; Khushaba et al., 2010; Kim et al., 2011; Li et al., 2010; Li et al., 2011; Tenore et al., 2009).

5. Conclusion

The complete and up-to-date 37 EMG feature extraction methods are proposed in review and theory. Redundancy of EMG features in time domain and frequency domain are pointed. Most time domain features show redundancy which can be seen in scatter graphs. They can be grouped into 4 main types based on mathematical properties: (1) energy and complexity information methods, (2) frequency information method, (3) prediction model method, and (4) time-dependence method. Features in the first two time-domain types show better performance than other last two groups. Recommendations of time domain features discussed by each type are MAV from energy information method, WL from complexity information method, WAMP from frequency information method, AR from prediction model method, and MAVS from time-dependence method. EMG features based on frequency domain are not good in EMG signal classification. Some frequency domain features have the same discrimination as features in time domain. MNF and PSR features are suggested to increase the ability of input vector for EMG signal classification. The results obtained from this study can be widely used and applied in many clinical and engineering applications.

Acknowledgements

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.eswa.2012.01.102.

References

Biopac Systems, Inc. (2010). EMG frequency signal analysis. <http://www.biopac.com/Manuals/app_pdf/app118.pdf>.

Boostani, R., & Moradi, M. H. (2003). Evaluation of the forearm EMG signal features for the control of a prosthetic hand. *Physiological Measurement, 24*(2), 309–319.

Du, S. (2003). Feature extraction for classification of prehensile electromyography patterns. Master's Thesis, San Diego State University, San Diego, CA, US.

Du, S., & Vuskovic, M. (2004). Temporal vs. spectral approach to feature extraction from prehensile EMG signals. In *Proceedings of IEEE International Conference on Information Reuse and Integration* (pp. 344–350).

Du, Y.-C., Lin, C.-H., Shyu, L.-Y., & Tainsong, C. (2010). Portable hand motion classifier for multi-channel surface electromyography recognition using grey relational analysis. *Expert Systems with Applications, 37*(6), 4283–4291.

Englehart, K., Hudgin, B., & Parker, P. A. (2001). A wavelet-based continuous classification scheme for multifunction myoelectric control. *IEEE Transactions on Biomedical Engineering, 48*(3), 302–311.

Farfán, F. D., Politti, J. C., & Felice, C. J. (2010). Evaluation of EMG processing techniques using information theory. *BioMedical Engineering OnLine, 9*(72). doi:10.1186/1475-925X-9-72.

Farina, D., & Merletti, R. (2000). Comparison of algorithms for estimation of EMG variables during voluntary isometric contractions. *Journal of Electromyography and Kinesiology, 10*(5), 337–349.

Fougner, A. (2007). Proportional myoelectric control of a multifunction upper limb prosthesis. Master's Thesis, Norwegian University of Science and Technology, Trondheim, Norway.

Graupe, D., & Cline, W. K. (1975). Functional separation of EMG signals via ARMA identification methods for prosthesis control purposes. *IEEE Transactions on Systems, Man and Cybernetics, SMC-5*(2), 252–259.

Gross, D., Grassino, A., Ross, W. R., & Macklem, P. T. (1979). Electromyogram pattern of diaphragmatic fatigue. *Journal of Applied Physiology, 46*(1), 1–7.

Han, J.-S., Song, W.-K., Kim, J.-S., Bang, W.-C., Lee, H., & Bien, Z. (2000). New EMG pattern recognition based on soft computing techniques and its application to control a rehabilitation robotic arm. In *Proceedings of 6th International Conference on Soft Computing* (pp. 890–897).

Hogan, N., & Mann, R. W. (1980). Myoelectric signal processing: Optimal estimation applied to electromyography-Part I: Derivation of the optimal myoprocessor. *IEEE Transactions on Biomedical Engineering, BME-27*(7), 382–395.

Huang, H.P., & Chen, C.Y. (1999). Development of a myoelectric discrimination system for a multi-degree prosthetic hand. In *Proceedings of IEEE International Conference on Robotics and Automation* (Vol. 3, pp. 2392–2397).

Hudgins, B., Parker, P., & Scott, R. (1993). A new strategy for multifunction myoelectric control. *IEEE Transactions on Biomedical Engineering, 40*(1), 82–94.

Kaufmann, P., Englehart, K., & Platzner, M. (2010). Fluctuating EMG signals: Investigating long-term effects of pattern matching algorithms. In *Proceedings of Annual International Conference of IEEE Engineering in Medicine and Biology Society* (pp. 6357–6360).

Khezri, M., & Jahed, M. (2009). An exploratory study to design a novel hand movement identification system. *Computers in Biology and Medicine, 39*(5), 433–442.

Khushaba, R. N., Al-Ani, A., & Al-Jumaily, A. (2010). Orthogonal fuzzy neighborhood discriminant analysis for multifunction myoelectric hand control. *IEEE Transactions on Biomedical Engineering, 57*(6), 1410–1419.

Kim, K. S., Choi, H. H., Moon, C. S., & Mun, C. W. (2011). Comparison of k-nearest neighbor, quadratic discriminant and linear discriminant analysis in classification of electromyogram signals based on the wrist-motion directions. *Current Applied Physics, 11*(3), 740–745.

Lei, M., Wang, Z., & Feng, Z. (2001). Detecting nonlinearity of action surface EMG signal. *Physics Letters A, 290*(5–6), 297–303.

Li, G., Li, Y., Yu, L., & Geng, Y. (2011). Conditioning and sampling issues of EMG signals in motion recognition of multifunctional myoelectric prostheses. *Annals of Biomedical Engineering.* doi:10.1007/s10439-011-0265-x.

Li, G., Schultz, A. E., & Kuiken, T. A. (2010). Quantifying pattern recognition—Based myoelectric control of multifunctional transradial prostheses. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 18*(2), 185–192.

Liu, X., Zhou, R., Yang, L., & Li, G. (2009). Performance of various EMG features in identifying ARM movements for control of multifunctional prostheses. In *Proceedings of IEEE Youth Conference on Information, Computing and Telecommunication* (pp. 287–290).

Merletti, R. (1996). Standards for reporting EMG data. *Journal of Electromyography and Kinesiology, 6*(1), III–IV.

Miller, C.J. (2008). Real-time feature extraction and classification of prehensile EMG signals. Master's Thesis, San Diego State University, San Diego, CA, US.

Oskoei, M.A., & Hu, H. (2006). GA-based feature subset selection for myoelectric classification. In *Proceedings of IEEE International Conference on Robotics Biomimetics* (pp. 1465–1470).

Oskoei, M. A., & Hu, H. (2007). Myoelectric control systems–A survey. *Biomedical Signal Processing and Control, 2*(4), 275–294.

Oskoei, M. A., & Hu, H. (2008). Support vector machine based classification scheme for myoelectric control applied to upper limb. *IEEE Transactions on Biomedical Engineering, 55*(8), 1956–1965.

Paiss, O., & Inbar, G. F. (1987). Autoregressive modeling of surface EMG and its spectrum with application to fatigue. *IEEE Transactions on Biomedical Engineering, BME-34*(10), 761–770.

Pandey, B., & Mishra, R. B. (2009). An integrated intelligent computing model for the interpretation of EMG based neuromuscular diseases. *Expert Systems with Applications, 36*(5), 9201–9213.

Park, S. H., & Lee, S. P. (1998). EMG pattern recognition based on artificial intelligence techniques. *IEEE Transactions on Rehabilitation Engineering, 6*(4), 400–405.

Philipson, L. (1987). The electromyographic signal used for control of upper extremity prostheses and for quantification of motor blockade during epidural anaesthesia. Ph.D. Thesis, Linköping University, Linköping, Sweden.

Phinyomark, A., Limsakul, C., & Phukpattaranont, P. (2009a). A novel feature extraction for robust EMG pattern recognition. *Journal of Computing, 1*(1), 71–80.

Phinyomark, A., Limsakul, C., & Phukpattaranont, P. (2009b). EMG feature extraction for tolerance of 50 Hz interference. In *Proceedings of 4th PSU-UNS International Conference on Engineering Technologies* (pp. 289–293).

Rafiee, J., Rafiee, M. A., Yavari, F., & Schoen, M. P. (2011). Feature extraction of forearm EMG signals for prosthetics. *Expert Systems with Applications, 38*(4), 4058–4067.

Saridis, G. N., & Gootee, T. P. (1982). EMG pattern analysis and classification for a prosthetic arm. *IEEE Transactions on Biomedical Engineering, BME-29*(6), 403–412.

Tenore, F. V. G., Ramos, A., Fahmy, A., Acharya, S., Etienne-Cummings, R., & Thakor, N. V. (2009). Decoding of individuated finger movements using surface electromyography. *IEEE Transactions on Biomedical Engineering, 56*(5), 1427–1434.

Tkach, D., Huang, H., & Kuiken, T. A. (2010). Study of stability of time-domain features for electromyographic pattern recognition. *Journal of NeuroEngineering and Rehabilitation, 7*(21). doi:10.1186/1743-0003-7-21.

Qingju, Z., & Zhizeng, L. (2006). Wavelet de-noising of electromyography. In *Proceedings of IEEE International Conference on Mechatronics Automation* (pp. 1553–1558).

Zardoshti-Kermani, M., Wheeler, B. C., Badie, K., & Hashemi, R. M. (1995). EMG feature evaluation for movement control of upper extremity prostheses. *IEEE Transactions on Rehabilitation Engineering, 3*(4), 324–333.

Zecca, M., Micera, S., Carrozza, M. C., & Dario, P. (2002). Control of multifunctional prosthetic hands by processing the electromyographic signal. *Critical Reviews in Biomedical Engineering, 30*(4–6), 459–485.