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Improving Class Separability of Frequency-domain Features for EMG Pattern Recognition

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Abstract

To apply electromyography (EMG) signals in human-computer interfaces, features extracted from raw EMG data are the significant stage to achieve the high classification accuracy in EMG pattern recognition. Although most of the successful features in the classification of movements associated with EMG signals are features calculated in time-domain, features extracted from frequency-domain are still necessary to yield maximum class separability in feature space. Due to a low quality feature space of frequency-domain EMG features, an addition of such features results in increasing a little classification accuracy. Hence, in this research, the improving quality of frequency-domain EMG features in space is presented. Wavelet packet transform method is used to make the useful sub-band EMG components. Four popular frequency-domain features, i.e. mean frequency (MNF), median frequency (MDF), peak frequency (PKF) and power spectrum ratio (PSR), were calculated from each sub-band EMG component and were evaluated their feature space quality using separability measure i.e. RES (the ratio of Euclidean distance and standard deviation) index. The experimental results showed that the classification performance of MNF and PKF extracted from the reconstructed EMG signal based on the 2nd level approximation 6th order Daubechies's wavelet coefficients was improved by twice compared with the traditional MNF and PKF. This finding was also found in the classification of MDF and PSR extracted from the reconstructed EMG signal based on the first level approximation coefficients with the 5th and the 7th order Daubechies wavelets, respectively. For single features, the proposed MDF outperforms others, and the accuracy (RES index = 10.71) is comparable to successful time-domain EMG features, such as mean absolute value (RES index = 8.93), zero crossing rate (RES index = 10.36), and waveform length (RES index = 11.68). As a single feature in EMG pattern recognition cannot reach the best performance and for a more powerful feature vector, the proposed MDF should be combined with other successful time-domain EMG features in future works.

Keywords: Electromyography signal; Feature extraction; Mean and median frequency; Myoelectric control systems; Wavelet analysis

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1. Introduction

Many input source of data or signals can be used for human-computer interfaces (HCIs). Surface electromyography (sEMG) signals generated by the human muscles are widely used in HCIs, particularly for powered upper-limb prostheses, electric power wheelchairs, and virtual keyboard and mouse [1]. To apply sEMG signals in HCIs, features extracted from raw sEMG data are the significant stage to achieve the high classification accuracy in EMG pattern recognition [2] because the raw sEMG data contain both useful and unwanted information. EMG features can be computed both in time domain and in frequency domain. Although most of the successful features in the classification of movements associated with EMG signals are time-domain features, frequency-domain features are still necessary to yield the maximum class separability in feature space [3]. However, an addition of frequency-domain EMG features results in increasing a little classification accuracy due to a low quality feature space of such features [4]. Hence, the quality of frequency-domain EMG features in space should be improved.

Based on one of our previous works [5], a discrete wavelet transform (DWT) method is used to generate a useful subset of frequency components (or scales) from sEMG signals. The results show that several time-domain features extracted from the suitable sub-band reconstructed sEMG signals yield improved class separability in feature space. However, the classification performance of frequency-domain features i.e. mean and median frequencies does not improve using the DWT method [6]. In this research, wavelet packet transform (WPT) method is used to make the useful sub-band EMG components.

Although DWT and WPT decompose the raw sEMG signal into some multi-resolution components according to a basis function called "wavelet function", the difference between DWT and WPT is that WPT offers more range of possibilities for signal analysis than DWT [7]. This may be a reason that the class separability of MNF and MDF features does not improve using DWT. Therefore, in this study the usefulness of extracting sub-band EMG components using WPT has been investigated and used instead of using DWT. Four popular frequency-domain features [3], i.e. MNF, MDF, peak frequency (PKF) and power spectrum ratio (PSR), were calculated from each sub-band EMG component and were evaluated their feature space quality using separability measure i.e. RES (the ratio of Euclidean distance and standard deviation) index [8].

2. Materials and Methods

Firstly, the description of sEMG data that were used to evaluate the proposed methods is presented. SEMG data recorded during six motions from two channels were used as a representative data. Secondly, the definition of four frequency-domain EMG features is provided in detail. Thirdly, the procedure of extracting the proposed frequency-domain features is presented together with the principle of wavelet transform. The evaluating function i.e. RES index is shown in the fourth sub-section.

2.1 SEMG data acquisition and experiments

The representative sEMG data were collected when the volunteer performed six motions: hand open (HO), hand close (HC), wrist flexion (WF), wrist extension (WE), forearm pronation (FP) and forearm supination (FS). Such motions are usually employed in the study of powered upper-limb prostheses [1, 3, 7]. Two muscles on forearm consisting flexor carpi radialis (FCR) and extensor carpi radialis longus (ECRL) were selected to provide both flexor and extensor muscles (or information). EMG data picked up by the disposal bipolar electrodes (3M Red Dot Monitoring Electrode 2223) on the right arm with an inter-electrode distance of 20 mm. In the experiment, ten datasets were collected for each motion with a duration of 256 ms. It should be noted that for the real-time response in myoelectric prosthesis control system, the response time should be less than 300 ms [1, 3, 7]. Hence, the EMG data in this study contain only short dynamic motions or transient signals. The measurement system was set the sampling frequency (f_s) at 1000 Hz, the resolution at 16 bits, the band-pass filter at 10-500 Hz, and the amplifier gain at 60-dB.

2.2 Frequency-domain EMG features

Frequency- (or spectral-) domain features are mostly deployed in the study of motor unit recruitment and muscle fatigue. However, frequency-domain features are still needful to provide useful information for the recognition of motions associated with sEMG signals. EMG information in frequency-domain can be provided by power spectral density (PSD). PSD can be estimated using either Periodogram or parametric methods i.e. the auto-regressive (AR) model [9]. Frequency-domain EMG features can be defined as the characteristic variables, such as mean, median, peak, or sum. The definition of all frequency-domain features is described in the following.

Mean frequency (MNF) is defined as sum of product of the EMG power spectrum and the frequency divided by total sum of the spectrum intensity [4]. This definition is also similar to the spectral center of gravity and central frequency (f_c) [10]. It is given by

$$MNF = \sum_{j=1}^{M} f_j P_j \left/ \sum_{j=1}^{M} P_j \right. , \qquad (1)$$

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

Median frequency (MDF) is defined as a frequency at which the EMG spectrum is divided into two regions with equal amplitude [4]. This definition is similar to a half of total power feature [3]. It is given by

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2} \sum_{j=1}^{M} P_j . \qquad (2)$$

Peak frequency (PKF) is defined as a frequency at which the maximum EMG power occurs [3].

$$PKF = \max(P_j), \quad j = 1,...,M . \qquad (3)$$

Power spectrum ratio (PSR) is defined as a ratio between the energy P_0 which is nearby the maximum value of EMG power spectrum and the energy P which is the whole energy of EMG power spectrum. PSR can be seen as an extension version of PKF and frequency ratio (FR) [11]. It can be defined as

$$PSR = \frac{P_0}{P} = \sum_{j=f_0-n}^{f_0+n} P_j \left/ \sum_{j=-\infty}^{\infty} P_j \right. , \qquad (4)$$

where f_0 is a feature value of the PKF and n is the integral limit. In this study, n is set at 20.

2.3 Sub-band EMG components using WPT

The extraction of traditional frequency-domain EMG features is generally calculated from the EMG power spectrum which is computed from the raw EMG signals. However, in this research, the EMG power spectrums P in all equations, *(1)-(4)*, were computed from the reconstructed EMG signals that were performed by the WPT method. The procedure of the proposed algorithm is shown in Fig. 1. However, two wavelet parameters, i.e. wavelet function and decomposition level, must be optimized to achieve the high performance of wavelet transform. These parameters are implemented in the wavelet decomposition and reconstruction steps as shown in Fig. 1. Nine sub-types of the Daubechies orthogonal wavelets (Db2-Db10) were selected together with four levels of decomposition to be evaluated in this experiment. The Daubechies (Db) wavelet family was suggested by several previous works as the most suitable wavelet for the analysis of sEMG signals [12, 13].
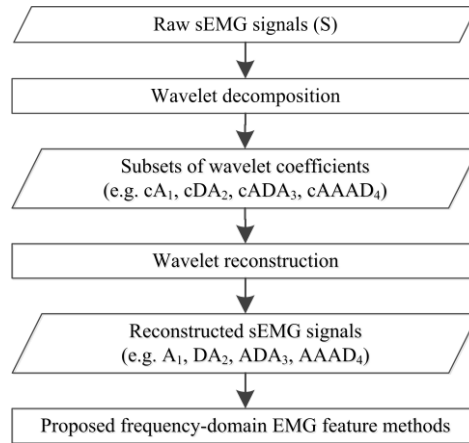
Fig. 1. The procedure of the extraction of frequency-domain EMG features from the reconstructed sEMG signals
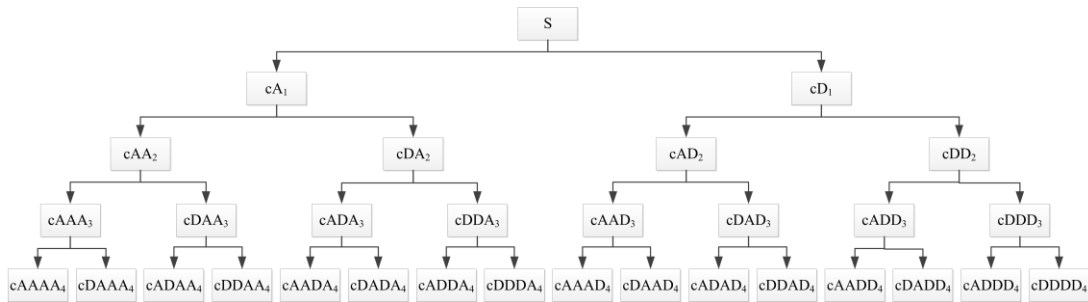

Fig. 2. WPT decomposition tree from 4 decomposition levels

To understand the usefulness of sub-band reconstructed sEMG signals, a brief description of WPT is presented. WPT iteratively transforms the sEMG signal into multi-resolution subsets of coefficients. Firstly, the raw sEMG (S) is passed through a high-pass filter and a low-pass filter to yield a detailed coefficient subset (cD1) and an approximation coefficient subset (cA1) at the first level, then both detailed and approximation coefficient subsets are performed the repetitious transformation to achieve a multi-resolution analysis. The process is duplicated until the desired final level is yielded. The coefficients of the filters depend on types of the wavelet function i.e. Db2-Db10.

It should be noticed that each of the wavelet coefficient subsets (2 from the first level, 4 from the second level, 8 from the third level, and 16 from the fourth level) is computed by using the inverse WPT method in order to obtain the reconstructed sEMG signals instead of computing from all the wavelet coefficient subsets as implemented in the traditional algorithm [5, 6]. Each subset has the different frequency contents. The frequency band of the approximation and detail coefficient subsets at the first level (cA_1 and cD_1) can be calculated as $f_{cA1} = [0, 2^{-2} \cdot f_s]$ and $f_{cD1} = [2^{-2} \cdot f_s, 2^{-1} \cdot f_s]$, where f_s is 1000 Hz. Each level increased, the frequency content of both frequency bands is reduced to half, for example, $f_{cD1} = [250, 500]$ Hz and thus $f_{cAD2} = [250, 375]$. In this study, all the calculations were computed using the MATLAB software.

2.4 Evaluating functions

Many previous works suggested [2, 14] that a high quality EMG features should have three properties: maximum class separability, robustness, and complexity. In this study, only the first property was focused. However, the development of the others can be found in one of our previous works [4]. While much of the work presented in literature focus on the evaluation of EMG features by imposing features onto the classifiers and

measuring the classification rate, the evaluation of EMG features by separability measure i.e. RES index is used in this study because the optimal features by using the first criterion depends on the classifier type [14].

RES index can investigate the distance between two scatter groups (a separation index) and directly address the variation of feature space in the same group (a compactness index) [15]. Each group refers to one of the combinations between six motions and two EMG channels. It is defined as the ratio of Euclidean distance and standard deviation. More details can be found in [8].

Table 1. The optimal wavelet component for each combination of 4 frequency-domain features (MNF, MDF, PKF, PSR) and 9 wavelet functions (Db2-Db10), and the baseline feature (extracting from raw sEMG data) with its RES index. Note that italic fonts and numbers show the highest RES index case.

MNF	**Baseline**	**Db2**	**Db3**	**Db4**	***Db5***	**Db6**	**Db7**	**Db8**	**Db9**	**Db10**
Component	All	AA_2	AA_2	AA_2	*AA_2*	A_1	AA_2	AA_2	AA_2	AA_2
RES index	5.48	9.09	8.09	9.21	*9.37*	8.64	8.89	9.11	8.76	9.04
MDF	**Baseline**	**Db2**	**Db3**	**Db4**	**Db5**	***Db6***	**Db7**	**Db8**	**Db9**	**Db10**
Component	All	AA_2	A_1	AA_2	AA_2	*A_1*	A_1	A_1	A_1	A_1
RES index	5.38	10.34	9.82	9.64	10.10	*10.71*	10.60	10.17	10.16	9.90
PKF	**Baseline**	**Db2**	**Db3**	**Db4**	***Db5***	**Db6**	**Db7**	**Db8**	**Db9**	**Db10**
Component	All	AA_2	AA_2	AA_2	*AA_2*	AA_2	AA_2	AA_2	AA_2	AAA_3
RES index	3.80	5.63	4.58	6.00	*6.39*	5.23	5.61	6.08	4.87	4.96
PSR	**Baseline**	**Db2**	**Db3**	**Db4**	**Db5**	**Db6**	***Db7***	**Db8**	**Db9**	**Db10**
Component	All	A_1	A_1	A_1	A_1	A_1	*A_1*	A_1	A_1	A_1
RES index	4.99	6.03	5.88	5.87	6.17	6.34	*6.55*	6.40	6.27	6.15

3. Results and Discussion

Table 1 shows RES indices for all features and wavelet functions with the optimal wavelet component. The experimental results clearly showed the effectiveness of the proposed algorithm for improving the class separability of frequency-domain EMG features. Several interesting points can be observed and summarized from the table as follows:

1) All features extracted from the reconstructed sEMG signals by the proposed algorithm, or WPT, always have the RES indices higher than that of features extracted from the raw sEMG signals (Baseline) for all wavelet functions (Db2-Db10). The difference between the RES indices of the best combination case and the baseline case ranged from 1.56 (PSR) to 5.33 (MDF). The classification performance of MDF extracted from the reconstructed sEMG signal based on the 1st level approximation 6th order Daubechies's wavelet coefficients was improved by twice compared with the traditional MDF.

2) Based on the comparison of four features, the RES indices that sorted in order from highest to lowest are 10.71 (MDF with A_1 of Db6), 9.37 (MNF with AA_2 of Db5), 6.55 (PSR with A_1 of Db7), and 6.39 (PKF with AA_2 of Db5). It means that MDF has the best performance, followed closely by MNF. PSR and PKF show worse classification performance compared to the first two features.

3) The optimal wavelet components for four features are the lower region of EMG spectrum: AA_2 (0-125 Hz) for MNF and PFK, and A_1 (0-250 Hz) for MDF and PSR. The finding results in this study are different compared to the results found in [16]. In that study, feature proposed is the spectral magnitude average (SMA). The SMA feature extracted from the EMG spectrum region (75-250 Hz) performs much better than the full spectrum (0-250 Hz). However, the EMG spectrum is computed by short-time Thomson transform (STTT).

To evaluate the results found in [16], the additional experiment was performed based on our proposed algorithm, or WPT. The results are shown in Table 2. From the table, it is obviously shown that the highest RES index is 10.83 in the case of DA_2 (125-250 Hz) with Db7. This finding is quite similar to the result found in [16]. However, as suggested in one of our previous works [3], SMA or mean power (MNP) feature has the same

cluster separability as time-domain features based on energy information but the quality of feature in space of SMA is lower than that of time-domain features. Therefore, SMA is not recommended to be deployed in the optimal feature vector.

Table 2. The optimal wavelet component for SMA with 9 wavelet functions (Db2-Db10), and the baseline feature (extracting from raw sEMG data) with its RES index. Note that italic fonts and numbers show the highest RES index case

SMA	Baseline	Db2	Db3	Db4	Db5	Db6	Db7	Db8	Db9	Db10
Component	All	DA_2	DD_2	D_1	D_1	DA_2	*DA_2*	DA_2	DA_2	DD_2
RES index	8.91	8.51	10.09	9.63	9.28	9.35	*10.83*	9.97	9.69	10.04

4) For single features, the proposed MDF feature outperforms others, and the classification performance is comparable to successful time-domain EMG features that are extracted from raw sEMG signals, such as mean absolute value (MAV), zero-crossing rate (ZCR), and waveform length (WL). The results are presented in Table 3.

As a single feature in EMG pattern recognition cannot reach the best performance and for a more powerful feature vector [1-3], the proposed MDF should be combined with other successful time-domain EMG features i.e. WL and ZC in future works.

Table 3. RES indices of 4 proposed frequency-domain features extracted from the optimal wavelet component and 3 traditional time-domain features consisting MAV, WL, and ZC

Feature	MNF	MDF	PKF	PSR	MAV	WL	ZC
EMG Data	AA_2 with Db5	A_1 with Db6	AA_2 with Db5	A_1 with Db7	Raw	Raw	Raw
RES index	9.37	10.71	6.39	6.55	8.93	11.68	10.36

4. Concluding Remarks and Future Works

The main benefit of WPT is that it generates a useful subset of frequency components. Noises and unwanted components were efficiently eliminated. Although most of the previous works used full EMG spectrum, in this study only the most effective spectrum component was used and performed much better than the traditional one. The reconstructed sEMG signals from the lower region of EMG spectrum are suitable for the extraction of frequency-domain features, particularly for the MDF feature.

In future works, the extraction of several successful time-domain EMG features based on the WPT method should be evaluated and the investigating the feasibility of implementing the proposed features in real-world applications should be done.

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