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CLASSIFICATION AND DETECTION OF THE HUMAN ACTIVITY BY ANALYZING EMG SIGNAL

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Abstract

The Electromyography (EMG) signal with broad applications in various areas especially in prosthetics and myoelectric control is one of the bio-signals utilized in helping humans to control equipments. In this study, measures of forearm surface EMG signals have been collected and processed, which is applicable to prosthetics. A statistical-based feature extraction system for forearm electromyographic (EMG) signals is proposed. In the first step, the CWT is employed to generate a wavelet decomposition tree and six features are extracted. In the second step, an algorithm based on statistical analysis method is introduced to compute the feature vectors for each forearm motion. This technique can successfully identify ten hand motions including forearm pronation (FP), forearm supination (FS), wrist flexion (WF), wrist extension (WE), wrist abduction (WAB), wrist adduction (WAD), key grip (KG), chuck grip (CG), spread fingers (SF), and a rest state (RS) including key grip and chuck grip, two motions known for their difficulty in classification. The results showed that proposed technique can achieve a classification recognition accuracy of over 96% for the eight hand motions.

Introduction

When a muscles contracts, myelectric potential occurs along the muscle fiber. EMG signal is measurable at a skin surface with non-invassive electrode. The signal contains the information about motion perform, such as the magnitude of muscle activity. Hence EMG signals are used to generate control commands for bio-control applications such as upper limb prostheses.

Much research is done on prosthetic hand has been on EMG analysis and its patter recognition, but only one particular joint prosthetic hand is in common use. Consider the commercial applicability of prosthetic hand, the research on multi-motion EMG hand is necessary. However, as the number of degree of freedom (DOF) increased, it was difficult to discriminate the operator's intended motion with sufficiently high accuracy due to their nonlinear and non-stationary of EMG characteristics. Here hand motion recognition method based on EMG signal using CWT with statistical based approach is used. Sensor selection method is also proposed to serve in real time approach.

A. Data Acquisition

The experimental surface EMG signals used in this study have been provided by the Institute of Biomedical Engineering at the University of New Brunswick with a protocol approved by the University's Research Ethics Board [1]. Especial data acquisition systems were used to collect surface EMG signals, a 16-electrode linear array with inter-electrode spacing of 2 cm was used (see Fig. 1). Each channel was filtered between 10 and 500 Hz and amplified with a gain of 2000. Typical surface EMG is shown in Fig. 2 for one subject.

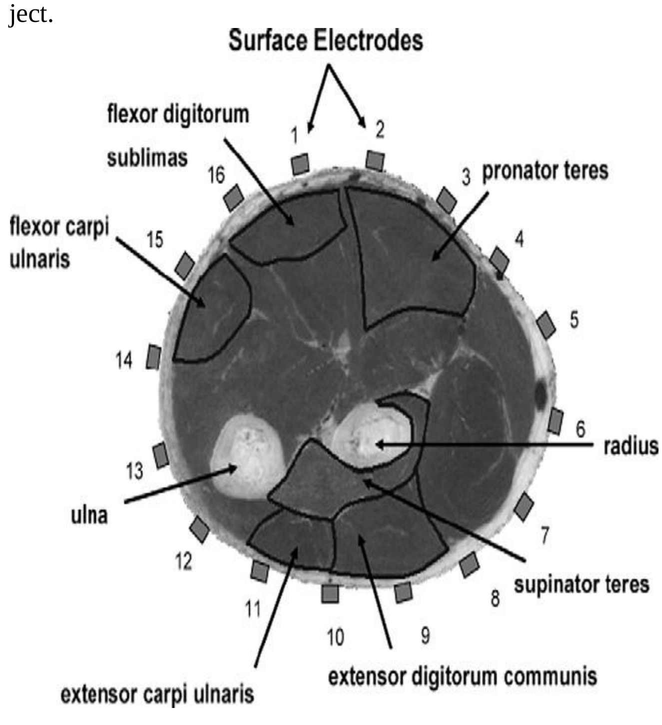

Figure 1. A cross section of the upper forearm to illustrate the locations of 16 surface electrodes and six needle electrodes

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These EMG signals were recorded in six subjects while they performed 10 hand movements for 5 second each, followed by a 2 minute resting period. All subjects denied fatigue during these exercises. The location of surface electrodes is depicted in Fig. 1 in a cross section of the forearm. The motions includes forearm pronation, forearm supination, wrist flexion, wrist extension, wrist abduction wrist adduction, key grip, chuck grip, hand open, and a rest state.

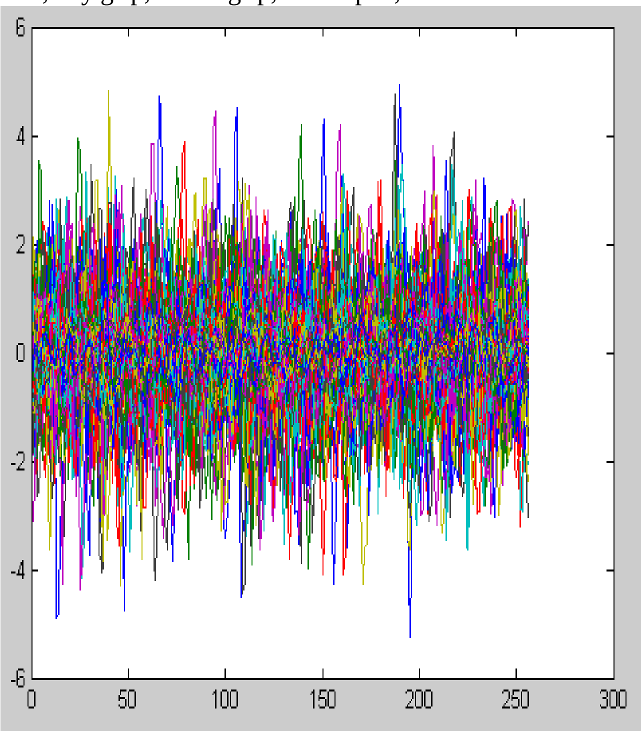

Figure 2. Typical Surface EMG for one subject

B. Wavelet Transform

Wavelet transform is being used in broad areas of biosignal processing. Wavelet transform is generally divided into either a discrete and or continuous form. The continuous wavelet transform (CWT) of a signal s(t) is defined as the integral of the product between the signal s(t) and the daughter wavelets, which are the time translation and scale expansion/compression versions of a mother wavelet function ψ (t). Equivalent to a scalar production, this calculation generates continuous wavelet coefficients CWC (a, b), which determine the similarity between the signal and the daughter wavelets located at position b (time shifting factor) and positive scale a:

$$CWC(a, b)= \int^{-\infty}_{+\infty} S(t)(1/\sqrt{a})\psi^*((t-b)/a)dt \quad (1)$$

Where * stands for complex conjugation and $\psi \in L^2(R)\backslash n \{0\}$. In the frequency domain, Equation (1) is expressed as:

$$F\{CWC(a,b)\}=\sqrt{a}\psi^*(a.\omega)S(\omega) \quad (2)$$

Where F {CWC (a, b)}, ψ *(ω), and S(ω) stand for the Fourier transforms of the continuous wavelet coefficients CWC (a, b), the signal S (t), and the mother wavelet function ψ (t), respectively. Equation. (2) shows that a mother wavelet function is a band-pass filter in the frequency domain, and the use of CWC identifies the local features of the signal. According to the theory of Fourier transform, the center frequency of the mother wavelet ψ (aω) is defined as F_0/a, given that the center frequency of the ψ (ω) is F_0. Consequently, extraction of frequency contents from the signal is possible in different scales. In the windowed Fourier transform, the frequency resolution is constant and depends on the width of window. However, wavelet transform offers a rich analysis for a wide variety of window widths as the function of a. Use of a wide variety of mother wavelet functions, which must satisfy the admissibility condition Cψ, is another advantage of wavelet analysis [5]:

$$C_\psi=\int^{-\infty}_{+\infty} (|\psi^*(\omega)|2)/\omega \, d\omega \ \alpha \ \infty \quad (3)$$

C_ψ is satisfied if the mean value of the mother wavelet function ψ(t), is equal to zero and ψ (t) decays to zero rapidly when $t\rightarrow \pm \infty$. If the mother wavelet satisfies the above condition as well as orthogonality, the signal can be reconstructed from wavelet coefficients.

Unlike DWT, CWT operates at any scale and is continuous in terms of shifting. In the calculation of CWC, the mother wavelet is shifted smoothly throughout the analyzed signal and gives rich time–frequency information. The main drawback of CWT is that the computation is time-consuming. For signals with low signal to noise ratio, CWT could work better than DWT because DWT down-sampling of the signals can lead to the loss of significant information. Wavelet decomposition of the signals is also divided into two main branches: pyramid and packet decompositions. In both methods, signals are divided into approximation (low frequencies) and detail (high frequencies) in the first level. In the pyramid decomposition, after the first level, only approximations are permitted to be decomposed through higher levels. However, in the packet decomposition both approximation and detail are decomposed into further levels. Therefore, packet decomposition offers rich contents of signals. For EMG signals, the significant frequency contents are achieved in high scales. Continuous wavelet transform, which means continuous shifting through time, is used with packet decomposition is used. Therefore, CWT converts a

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one-dimensional signal s (t) into a matrix of CWC (a, b) as follows:

$$CWC\,(a, b) = T_s /(\sqrt{|a|}) \sum_{n=0}^{N-1} \psi^*[(n-i)T_s/a]S(nTs) \qquad (4)$$

where i = 0,1,2,. . .,N, Ts is sampling time and N stand for the number of samples, respectively.

In classification, feature vector is defined as a compressed, meaningful vector possessing the significant information of different classes. Here CWC is used for the calculation of feature vectors for EMG signals. The CWC of the signal, itself, is not appropriate as a feature vector because it is computationally expensive. Hence, further processing is needed in order to define a precise and compressed feature vector, which is explained in the next section.

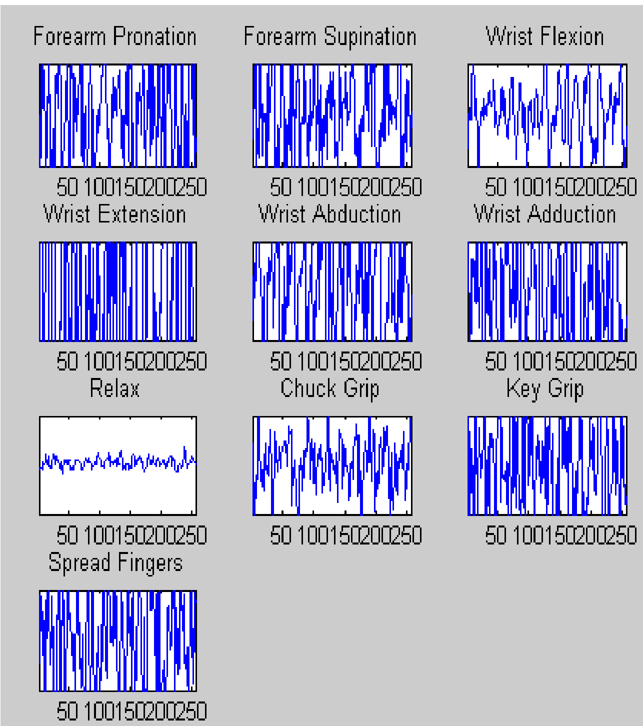

Figure 3. Segmented Surface EMG signals in a 256-points window from one subject performing 10 different hand motions

C. Mother Wavelet Matrix and Sensor Selection

Selection of the mother wavelet function is a challenge in wavelet transform. Two points regarding the application of mother functions are discussed here. The first concern is the selection of proper mother wavelet function since the application of mother wavelets is problem-dependent. Applicable mother wavelet functions in EMG signal processing could vary depending on the parameters of the problem at hand. If the technique is based on the similarity of the signal to the mother function, then the most important factor is the amplitude of the wavelet coefficient across the signals. The mother functions similar to the signal are not suitable for all wavelet based approaches. A clear example is the wide application of the Haar function, which is dissimilar to the signals but has been introduced as a relatively efficient function in several studies. In wavelet-based classification systems the mother wavelet functions are related to the problem parameters rather than the shape of signals, unless the method was established based on signal similarity. Another issue in EMG signals classification is the optimal sensor selection. Applicable sensor selection depends on the problem as well. For example, optimal selection of sensors for prosthetic hands to classify six motions is different from those for eight motions. To reduce the computational time for real-time control of a prosthetic hand, the optimal electrodes to be chosen are presented for the ten motions classification by introducing surface electrode matrix (SEM).

D. Feature Vector Algorithm

First, the feature vector is defined based on the following steps: 1] Signal segmentation: Here surface EMG signals are classified for ten hand motions, after recording EMG signals by means of sixteen electrodes for surface, the raw signals were segmented into the 256-point windows for surface EMG signals. For simplicity, a signal with a length of 256 points is called the segmented signal. Therefore, a matrix of segmented signals is 16 X 256 metrics and can be one input for the control system of prosthetic hand.

2] In the fourth decomposition level, continuous wavelet coefficients of the segmented signals (CWC-SS) were calculated (24 scales for each segmented unit signal).

3] The average of the absolute value of the segmented signals (1 X 256 vectors) were calculated for each segmented signal and titled ‘weight’ (W) to construct the feature vector as follows:

$$W = (1/N) \sum_{i=1}^{N} |\, Si\,(t)\, | \qquad (4)$$

Where N is the number of data points in each segmented signal (256).

4] The calculation of feature vectors – six feature vectors are:

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A] Weighted sum of absolute value of CWC-SS (SA) is calculated as the sum of the absolute value of CWC-SS multiplied by the average of the absolute value of the segmented signals (weight).

$$SA(a15,b)=W(\sum_{n=1}^{N}|CWC(a15,b)|) \qquad (5)$$

where a15 is the scale related to (4, 15) from decomposition tree. Scale selection is another important issue in wavelet analysis. Decomposing the signals into higher scales leads to a greater focus on the frequency domain. Nevertheless, computational time in CWT is of paramount significance, and going through high scales makes the computations for the real-time control system of the prosthetic hand difficult. The fourth level of decomposition has been considered the reasonable level. Based on trial-and-error, a15 represented larger wavelet coefficients, and subsequently the daughter wavelet at this scale is more similar to both classes of EMG signals, which, at that scale, leads to a greater difference in the wavelet coefficient from one motion to another [2].

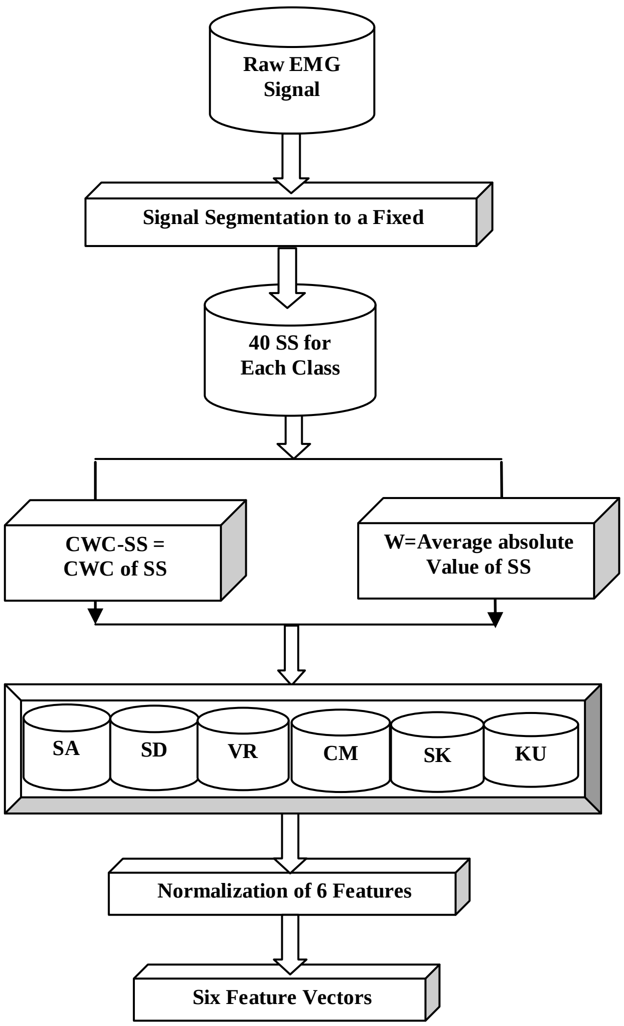

Figure 4. Feature Extraction Algorithm

B] Weighted standard deviation of CWC-SS (SD) is calculated as the standard deviation of CWC-SS multiplied by the average of the absolute value of the segmented signals (weight).

$$SD(a_{15},b)=W(\sqrt{}(1/(N-1)\sum(CWC_n(a_{15},b)-(CWC(a_{15},b))^2 \qquad (6)$$

$$\text{Where } (CWC(a_{15},b))=(1/(N-1))(\sum(CWC_n(a_{15},b)) \qquad (7)$$

C] Weighted variance of CWC-SS (VR) is calculated as the variance of CWC-SS multiplied by weight, as the last steps for SD and SA are defined.

D] Weighted fourth central moment of CWC-SS (CM) is calculated as the fourth central moment of CWC-SS multiplied by weight. The basic formula is not included for simplicity.

E] Weighted skewness of CWC-SS (SK) is calculated as the skewness of CWC-SS multiplied by weight.

F] Weighted kurtosis of CWC-SS (KU) is calculated as the kurtosis of CWC-SS multiplied by weight.

5] All these features are normalized to make the calculations consistent. SA feature was one of the features showing better classification performance for surface EMG signals. Therefore, SA is mainly considered to define the mother wavelet matrix.

The feature obtained from above steps will be used for identification of corresponding activity of the subject [1, 2 and 4].

E. Matrix Formation Algorithm

After selection of the feature, the following procedure is applied to find the MWM and SEM:

For each pair of motions the corresponding entity of MWM matrix is the function ψ that possesses the minimum value for the criterion C(ψ):

$$\forall i,j=1,\ldots\ldots.10 \text{ and } i\neq j\, MWM(I,j)= \psi{:}\min_{\psi}[(1/L)\sum_{l=1}^{L}Dl(\psi)] \qquad (9)$$

where L is the number of the electrodes and ψ is selected from a pool of 324 wavelet basis function.

$$D_l(\psi) = (R_i(\psi)+R_j(\psi))/(|M_i(\psi) - M_j(\psi)|) \qquad (10)$$

where $R_i(\psi)$ is the range of SA function for all k = 1, . . .N, and N = 240 segmented signals for i^{th} motion (N = 240 since there are six subjects and 40 segmented signals for each subject):

$$R_i(\psi) = |\min_k(SA_{ik}(\psi)) - \max_k(SA_{ik}(\psi))| \quad (11)$$

In Equation (10), $M_i(\psi)$ is the average value of SA function for all
k = 1,. . .,N segmented signals for i^{th} motion:

$$M_i(\psi) = (1/k)\sum_{k=1}^{N} SA_{ik}(\psi) \quad (12)$$

where $SA_{ik}(\psi)$ is the value of SA function for i^{th} motion and kth segmented signal calculated by Equation (6). By minimizing the value of C (ψ) and therefore the value of D_l (ψ) for each pair of motions, the mother wavelet having the less range of feature values for N segmented signals and more difference between two motions is selected. After finding MWM matrix, SEM matrices can be obtained. For each pair of motions, the corresponding entity of SEM matrix is the surface electrode number, which has the minimum value of $D_l(\psi)$ function as Equation (10) calculated for corresponding mother wavelet extracted from MWM matrix.

F. Discussion

At this juncture six statistical features are studied for surface EMG signals for one specific scale recorded from a

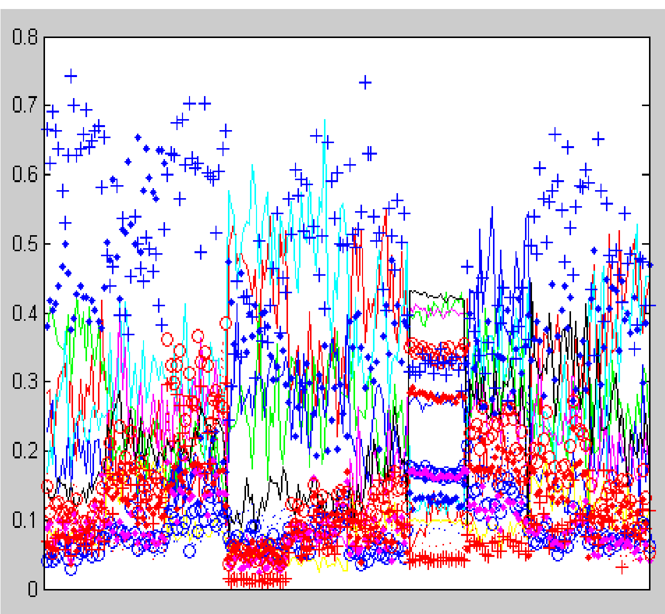

Figure 5. Ten hand activities of one of the subject

specific sensor attached to the arm of one subject. Among the features, SK and KU did not show proper classification for this scale/sensor and neither for the others. The other four features can be useful for forearm EMG signal classification. It is worth mentioning that CM feature cannot visually show proper classification. However, by zooming on the CM plot, more information may be observed. Also, mother wavelet matrices (MWM) matched with our experimental data surface EMG sign.

The advantages of the proposed technique can be summarized as follows:

1. The number of motions is increased to ten hand motions. Chuck and key grips, which are the complicated motions for classification because of the engagements of several in-depth muscles and complexity of the signals, are studied by the proposed algorithm.
2. The presented features would also be appropriate for training purposes of intelligent classifiers or to determine rules for fuzzy systems.
3. This method is able to find optimal sensors for each pair of motions applicable for classification purposes.

Conclusion

A method suggested extracting appropriate features for forearm electromyographic (EMG) signals using a mother wavelet matrix (MWM). After broad investigations on 324 mother wavelet functions, the combination of some mother wavelets ameliorated the EMG signal analysis. Among several installed electrodes on the subjects' forearms, the optimal sensors appropriate for feature extraction were selected in terms of surface electrode matrix (SEM). Six statistical feature vectors are also studied.

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