Analysis of sEMG to remove ECG using wavelets

Mr. Y. Dileep Kumar and Dr. A. M. Prasad

Introduction

Surface electromyography (EMG) is a noninvasive technique for recording the electrical activity associated with skeletal muscles. Surface electromyography (EMG) has been commonly used to assess the neuromuscular demand on muscles while performing various tasks and is being rapidly introduced to the field of health care. Electromyography (EMG) is the measuring of the electrical activity associated with the contraction of skeletal muscles in the body. SEMG is the noninvasive measurement of EMG from the surface of the skin. Currently, sEMG is used in ergonomic studies, exercise physiology, movement and gait analysis, rehabilitation, biofeedback, powered control of prostheses, and clinical neuromuscular assessment. Acquired sEMG signals are susceptible to various forms of contamination which can invalidate conclusions drawn from the data. Power line interference, motion artifact, or ECG interference are the main artifacts in the EMG. There are many methods for denoising, but discrete wavelet and wavelet denoised techniques are the improved methods for the above problems. The electrocardiogram signal which represents the electrical activity of the heart provides interference in the recording of the electromyogram signal, when the electromyogram signal is recorded from muscles close to the heart. Therefore, due to impurities, electromyogram signals recorded from this area cannot be used.

The amplitude of the EMG signal is within a range from the $\mu$V to low mV (0-6 mV peak-to-peak or 0-1.5 mV RMS). The energetic distribution of EMG signal is basically within the 0 to 500 Hz range in frequency domain, with the dominant components in the 50-150 Hz range. Outside the 0-500 Hz frequency range, signals with energy less than electrical noise level are unusable. The frequency content range of the ECG signal is between 0.1 Hz and 45 Hz. Also, the ECG signal amplitude is in a range of mill volt and in some cases, is several times larger than the EMG signal amplitude. ECG is used to diagnose some diseases such as low back pain, control of neural prostheses and feature extraction of hand motion and especially for our goal, hand motion prediction and after that hand motion control.

Methodology:

A. Data:

To test the proposed method a simulation was performed. Pure EMG data were simulated with an impulse train of changing random amplitude (Fig 2). ECG noise (Fig 3) was separately built and added to EMG after filtering. This filtering was a
representation of body impedance, which is very hard to estimate. FIR filter of length 40 in this simulation was employed. Figure 4 shows the simulated noisy signal. To consider PLI, a 50 Hz sinusoidal signal and its harmonics were added to EMG signal as well.

**B. Processing of emg signals:**

The signal is amplified, and usually filtered and then processed. The result of these actions is to produce a time varying electrical voltage which can be displayed to the patient by means of a series of lights, varying tones, and numbers on the LED display or through a computer link once it has been converted from an analogue to a digital form. Although this electrical processing means that the patient does not get to see their 'real' electrical muscle activity, it is actually more useful in its processed form. The graphs below illustrate the results of these processes on a simple EMG recording. Electrical artifacts (electrocardiogram, ECG) produced by the heart may contaminate electromyogram (EMG) signals when recording surface EMG from torso muscles. This source of noise is a big concern for myoelectric prosthesis control in a patient with bilateral amputations at shoulder disarticulation level, where the control signals are taken from the reinnervated pectoralis muscles of the patient. Compared with surface EMG, ECG signal contains relatively low frequency components. ECG noise removal from EMG signal method based on recently developed wavelet analysis. The proposed wavelet analysis based method is able to remove low frequency noise such as ECG signal. The method is validated through experiments on the MIT-BH databases. Both quantitative and qualitative results are given. The simulations show that the proposed wavelet analysis provides very good results for de-noising.

**Fig. 1:** simulated EMG.

**Fig. 2:** simulated ECG.

**Fig. 3:** simulated contaminated EMG.

**Fig. 4:** block diagram of removal of ECG noise from contaminated EMG.

**Fig. 5:** Lab view block diagram of EMG analysis and EMG peak detection.
C. Feature extraction:

Feature extraction plays a very significant role in EMG classification because even the best classifiers cannot perform well if they are not fed with proper features. In another word, useful information that are hidden in EMG signal are extracted in feature extraction and in this way, unwanted parts of the signal are removed. In our study, WT has been applied to find the desired features which have been defined as Mean Absolute Value (MAV) of SEMG. Since WT lead us to different frequency components through using appropriate function as mother wavelet, getting the most significant information of EMG signal spend less time and computation. The various features extracted by different researchers are mean absolute value (MAV), variance (VAR), standard deviation (SD), zero crossing (ZC), waveform length (WL), Willson amplitude (WA), mean absolute value slope (MAVS), mean frequency (MNF), median frequency (MDF), slope sign change (SSC), cepstrum coefficients (CC), fast Fourier transform (FFT) coefficients, short time Fourier transform (STFT) coefficients, root mean square (RMS), autoregression (AR) coefficients, integrated EMG (IEMG), wavelet transform (WT) coefficients, and wavelet packet transform (WPT) coefficients. In this work the feature extracted are Mean absolute values, Root Mean Square Mean Frequency, Zero crossing, Slope Sign Change, Standard deviation. These features are extracted for every movements and the calculation is given below.

(i) Mean Absolute Value (MAV):

It is the average rectified value (ARV) and can be calculated using the moving average of full-wave rectified EMG. More specifically, it is calculated by taking the average of the absolute value of EMG signal. It represents the simple way to detect muscle contraction levels. It is calculated as

\[ \text{MAV} = \frac{1}{N} \sum_{i=1}^{N} |x_n| \]

(ii) Root Mean Square (RMS):

It is represented as amplitude modulated Gaussian random process whose RMS is related to the constant force and non-fatiguing contraction. It can be expressed as

\[ \text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_n^2} \]

(iii) Standard Deviation (SD):

It can be used to find the threshold level of muscle contraction activity. The general equation used to find SD by

\[ SD = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x_n - \bar{x})^2} \]

III. Filter And Wavelet Analysis:

The wavelet transform uses a short time interval for evaluating higher frequencies and a long time interval for lower frequencies. Due to this property, high frequency components of short duration can be observed successfully by wavelet transform. Here we have used discrete wavelet transform (DWT) to extract relevant information from the EMG signal. DWT performs a multilevel one-dimensional wavelet analysis using either a specific wavelet or specific wavelet decomposition filters; the definition of DWT is given as where * denotes complex conjugation and, (ѱ)a b(t) is a window function called the mother wavelet, a is a scale factor b is a translation factor. Here is a shifted and scaled version of a mother wavelet which is used as bases for wavelet decomposition of the input signal. A good mother wavelet is one which has ability to fully reconstruct the signal from the decompositions. The selection of relevant wavelet is an important task before starting the detection procedure. The choice of wavelet depends upon the type of signal to be analyzed. The wavelet similar to the signal is usually selected. This similarity can also be decided on the basis of the cross-correlation between the two functions. There are several wavelet families like Harr, Daubechies, Biorthogonal, Coiflets, symlets, Morlet, Mexican Hat, Meyer etc. and several other real and complex wavelets. However, Daubechies (Db2, Db6, and Db8) wavelet has been found to give details more accurately than others. Moreover, this wavelet shows similarity with signal complexes. Therefore, we have Daubechies (Db2) wavelet for extracting EMG features in our application.

![Fig. 6: lab view block diagram of simulated EMG signal with digital filters and band pass filters.](image-url)
IV. Results:

Results show that we can successfully eliminate ECG noise by using wavelet denoised for different subjects. Power spectrum density of the contaminated EMG signal, and the cleaned EMG shows that the 50 Hz and its harmonics are extracted from the signal. Displays the effect of wavelets to cancel ECG noise from our simulated data. Please note that the contaminated red signal has consequent peaks, which are seen as vertical abruptions; however, the denoised signal does not include this effect. Figure shows the power spectrum of simulated noisy EMG and denoised signal in the frequency domain. Power spectrum of noisy signal is higher due to cardiac noise as well as PLI. It has sharp maximums at frequencies of 50 Hz and its harmonics due to PLI, which are removed after filtering.

Conclusion:

Heart-induced artifacts in an EMG from the trunk muscles of SCI patient shinders the accurate assessment of the valuable clinical information provided by the EMG. Current filtering techniques, which use global filtering or adaptive filtering principles, are not able to effectively de-noise the EMG, i.e. remove the ECG-related corruption. As shown by our analysis, wavelets using the Morlet Wavelet and Daubechies Transformation are significantly more effective than traditional filters for preserving the native EMG signal. Therefore, the proposed framework is cap- able of effectively eliminating the ECG artifacts from an EMG signal. This method can be used clinically in order to precisely quantify the respiratory motor function in patients with SCI or other disorders who tend to produce low EMG activity.
ACKNOWLEDGMENT

The authors would like to acknowledge the Department of Electronics and Instrumentation Engineering, Sree Vidyanikethan Engineering College, Tirupati-517102, AP, India and Electronics and Communication Engineering Department, JNTUK, Kakinada-533003, AP, India for providing the facilities to carry out this work.

REFERENCES


