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De-noising and Feature Extraction of ECG and EEG Signal Using Adaptive Algorithm and Wavelet Transform

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Abstract

Frequency of Biomedical signals are low, hence contaminated by surrounding environmental signal and interfered by other biomedical signal of same person, conducted through his body. The main objective of this paper is to eliminate both the noise and interference part of the biomedical signal using adaptive algorithm. Here, we consider two signals: ECG (Electrocardiography) and EEG (Electroencephalography) where the most adverse situation of first one take place when mother's ECG is interfered by the fetus ECG and the second one is heavily interfered by ocular movements. Here we have considered only LMS (Least Mean Square) algorithm to recover the original ECG and EEG signals instead of other complex adaptive algorithm to avoid unnecessary time complexity on such low frequency signal. The scalogram of both ECG and EEG signals are determined applying, continuous wavelet transform (CWT) to extract features of both signals. The phase error between original and recovered signal is also determined by CWT and very small phase error is found at low scale level of the signal. We applied eight different types of wavelet functions and found the most distinct results of ECG for 'Mexican Hat' function but for the case of EEG the Meyer, Symlet8, Daubechies8 wavelets provides the most distinct scalogram, can be applied in diagnostics.

Keywords: DWT, LMS algorithm, Scalogram, EOG and Coherence signal.

Introduction

Signal based medical diagnostics are done in several ways like: electromechanical, electrochemical, electrophysiological or electromagnetic actions of the body. All of above provides the signal called biomedical signal provide some features pertinent to condition of human body discussed in [1-3]. All the biomedical signals are of low frequency signal have the chance to be contaminated by environmental phenomena (noise) or manmade signal (interferences). For example, the electrocardiogram (ECG) recorded from the chest may be contaminated with artifacts and the 60Hz power line signal, the electroencephalogram

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(EEG) recorded from the scalp of a volunteer may be contaminated by the electrophysiological activity of the heart or movement of eyes.

One of the simplest adaptive algorithms in de-noising of signal is Least Mean Square (LMS) algorithm. The process time and performance of the algorithm are governed by the step size in updating weighting factor. In [4], variable step size algorithms are used to eliminate artifacts in ECG. In [5] the noise of EEG is removed, using Recursive Least Square (RLS) algorithm. Four different types of noise are considered and the performance of the algorithm is measured in terms of SNR before and after filtering. The performance of Kalman filter is better than RLS, LMS or FDAF at the expense of process time. De-nosing of ECG signal is done by Kalman filter in [6] and similar job is done by extended Kalman filter in [7]. The parameters used to measure the performance of the filter are, mean square error (MSE) and peak signal to noise ratio (PSNR). In [8], the real time EEG signal is extracted by Digital Signal Processor (DSP) board of Texas TMS320C6711. Finally, the low frequency power line signal (50 Hz) is removed by Kaiser window based FIR notch filter. The verification of removal of 50Hz power line signal is done by applying FFT on EEG signal.

One of the prominent methodologies of de-noising of image or time varying signal is DWT; where filter bank is used with threshold value at the output of LP and HP analysis filter. In [9] Un-decimated Wavelet Transform (UWT) is used for de-noising ECG signal; where Coiflet and Daubechies filter is chosen as the component of filter bank. In [10] White Gaussian noise of ECG is removed significantly applying Discrete Wavelet Transform with thresholding (soft and hard) techniques. The authors use Daubechies wavelet function with three level decomposition of filter bank. Same parameters of [7], are used to measure performance of recovered signal.

A comparison of DWT and adaptive neuro-fuzzy inference system (ANFIS) is made in [9] in de-noising ECG. The comparison is made in context of: mean error, maximum error, variance of noise and process time. The ANFIS is found better for the case of mean error but DWT is better in consideration of process time.

The entire paper is organized as: section 2 provides basic theory of adaptive algorithm and continuous wavelet transform, section 3 deals with experimental setup of extraction of ECG and EEG signals, section 4 provides the results based on analysis of section 3 and section 5 concludes entire analysis.

Basic Theory

In this paper we use LMS algorithm and continuous wavelet transform to recover the biomedical signals from a noisy environment and extraction of their features. The simplest adaptive algorithm to update the coefficients a digital filter is LMS algorithm. The steps of LMS algorithm are:

- ✓ Initially, set the weight $w_k(i)$, $i = 0,1, \ldots, N$-1, where k is sampling instant.
- ✓ Compute the output of filter, $\hat{n}_k = \sum_{i=0}^{N-1} w(i) x_{k-i}$
- ✓ The error weights, $e_k = y_k - \hat{n}_k$
- ✓ Update the next filter weights

$$w_{k+1}(i) = w_k(i) + 2\,\mu e_k x_{k-i} \tag{1}$$

;where μ is the step size of the adaptive filter. Details of the algorithm and its applications are found in [12-13].

We have also used the concept of continuous wavelet transform (CWT) to achieve the features of biomedical signal. Wavelet is an oscillatory function of finite duration is used as the basis function in CWT. The continuous wavelet transform (CWT) is used to analyze the frequency content of a signal with its changes over time. Let *f(t)* be any square integral function. The CWT or continuous-time wavelet transform of *f(t)* with respect to a wavelet $\psi(t)$ is defined as,

$$W(a,b) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{|a|}} \psi^*\left(\frac{t-b}{a}\right) dt \tag{2}$$

Where *a* and *b* are real and * denotes conjugation.

Equation (2) can be written in a more compact form by defining,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{3}$$

Combining (2) and (3),

$$W(a,b) = \int_{-\infty}^{\infty} f(t)\psi_{a,b}(t)dt \tag{4}$$

Inverse CWT operation can be expressed like,

$$f(t) = \frac{1}{C}\int_{a=-\infty}^{\infty}\int_{b=-\infty}^{\infty}\frac{1}{a^2}W(a,b)\psi_{a,b}(t)dadb \tag{5}$$

;where $C = \int_{-\infty}^{\infty}\frac{|\psi(\omega)|^2}{|\omega|}d\omega$, $\psi(t) \leftrightarrow \psi(\omega)$ and $0 < C < \infty$

The details analysis of wavelet transform and applications are available in [14-15].

System Model

De-noising of maternal ECG from noisy signal contaminated by correlated fetal ECG

In a typical biomedical application, signal processing may include four stages: data acquisition, signal conditioning, feature extraction, and decision making. For pregnant woman, the mother's ECG is interfered by fetal ECG. The fetal ECG is captured from mother's abdomen by an array of electrodes. The mother's own ECG is extracted in a conventional technique. A component of mother's ECG signal is highly correlated with the fetal ECG since the body of mother works as the channel between these two signals. Although both the signal are contaminated by background noise but main challenge is to segregate two ECGs. The arrangement of adaptive filter in retrieving pure Maternal ECG is shown in Figure 1 as shown in [16-17].

The steps of algorithm of de-noising maternal ECG from fetal ECG signal using adaptive algorithm and feature extraction using continuous wavelet transform is given below.

- Read chest leads of ECG as the noisy signal ($s + n$) and the abdominal leads as the source of noise $\acute{n}$.

- Preprocess both the signals by band pass filter to avoid white noise outside the bandwidth.
- Considering $(s + n)$ and $\acute{n}$ as the input signal, determine error signal, $e = (s + n) - \acute{n}$ as the maternal ECG.
- Apply moving average to smooth maternal ECG signal.
- Apply continuous wavelet transform to extract features from the recovered signal.

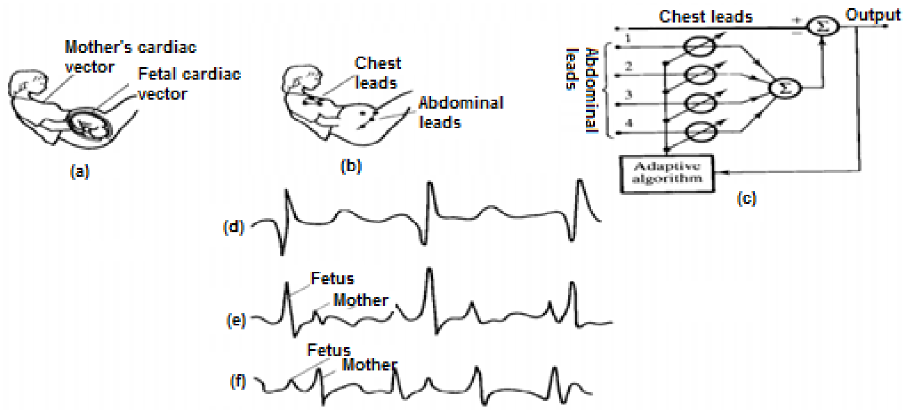


Figure 1: Adaptive extraction of Maternal ECG [16-17]: (a) cardiac electric field vectors of mother and fetus; (b) placement of leads; (c) adaptive filter; (d) idealized fetal ECG(abdominal leads); (e) idealized contaminated mother's ECG (chest leads); (f) output of noise canceller throwing reduced mother's ECG

De-noising of EEG from noisy signal contaminated by ocular artifact

The EEG is the flow of electrical signal on the human scalp generated by electrical activity of brain. The movement of human eyes produce electrical potentials around the eyes called the electrooculogram (EOG) which spreads across the scalp hence contaminates the EEG. The signal taken from the scalp is combination of EEG and EOG. The signal taken around eyes is mainly EOG which is correlated with one portion of scalp signal. Therefore adaptive algorithm can be applied to remove EOG from the signal of scalp. The complete arrangement of adaptive filter in elimination of EOG is shown in Figure 2.

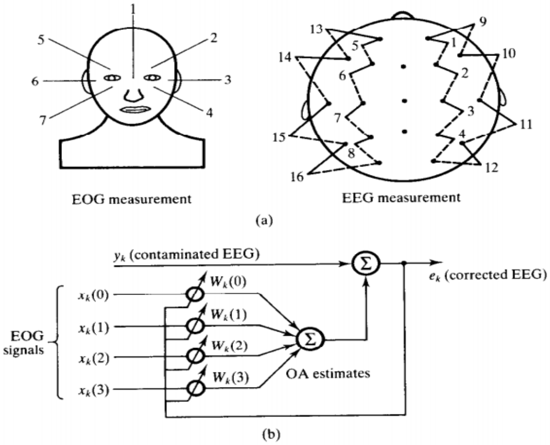


Figure 2: Adaptive extraction of EEG from ocular artifact [16]. (a) leads placement in human scalp (b) adaptive filter for throwing away ocular artifacts.

The steps of algorithm of de-noising EEG signal using adaptive algorithm and feature extraction using continuous wavelet transform is given below.

- Read back head leads of EEG as noisy signal ($s + n$) and forehead leads as the source of noise $\acute{n}$.
- Preprocess both signals by band pass filter to avoid white noise out the bandwidth.
- Apply adaptive algorithm to recover the original EEG.
- Compare measured and desired EEG signal.
- Apply continuous wavelet transform to extract features of the recovered signal

The next section will deal with the results based on analysis of section 3.

Results

First, we apply LMS algorithm to segregate maternal ECG from its contaminated version. The results as shown in Figure 3; where the recovered signal resembles to the original signal. Again, retrieve of original EEG signal from its contaminated version is shown in Figure 4 using the same adaptive algorithm.

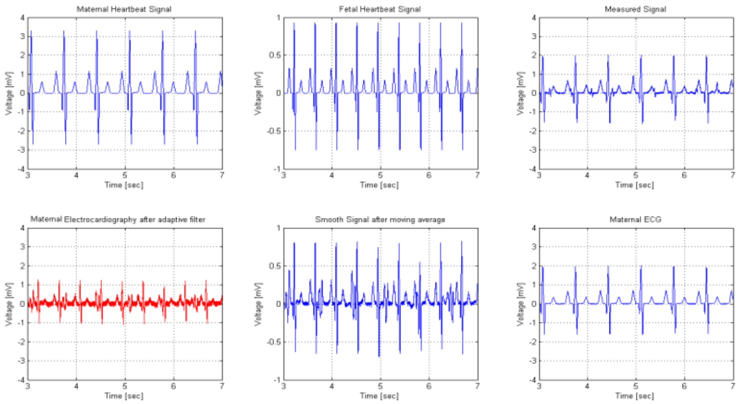


Figure 3: De-noising of maternal ECG from fetal ECG using adaptive algorithm.

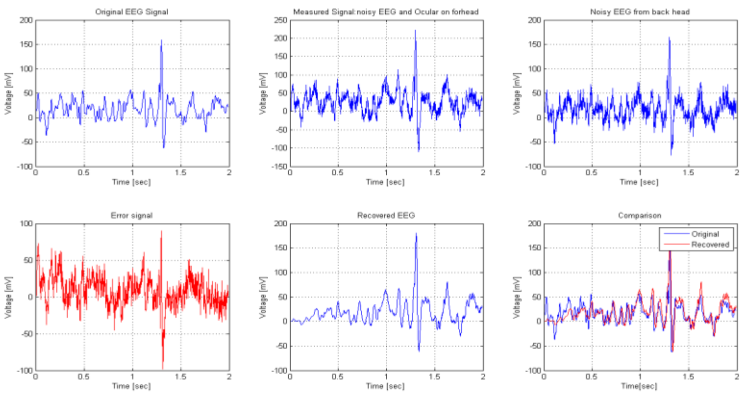
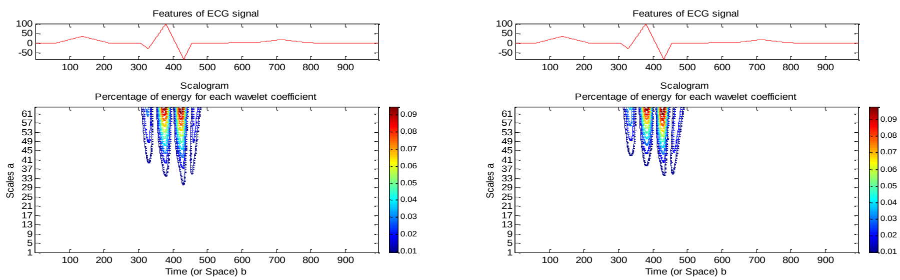


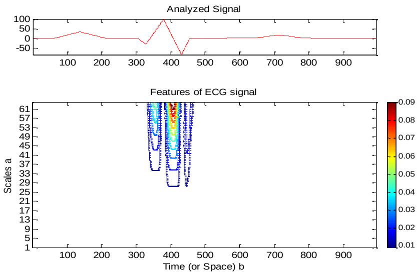
Figure 4: De-noising of EEG signal from ocular artifact using adaptive algorithm.

In [19] de-noising of EEG is done by filter bank of DWT and that of ECG is found in [20]. Here our next job is to extract features of ECG and EEG signal using continuous wavelet transform. Any signal is constructed by superposition of scaling and translated version of basis function. The coefficients of CWT or DWT are the cross correlation coefficients between the wavelet basis function and the signal; varying scaling and shift parameter of the wavelet basis. The original signal is reconstructed as the weighted sum of the basis function for all-possible scaling and corresponding shifts till the length of the signal; where the weights are the wavelet coefficients.

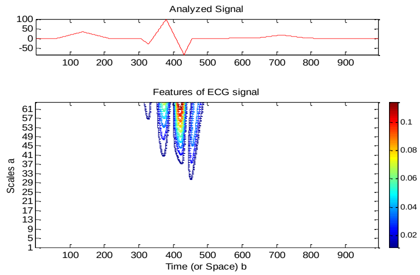
We have to locate the position and amplitude of the maxima of a signal from the coefficients of CWT of the signal. The wavelet transform is very essential in detecting abrupt changes in a signal, which bears the feature of a signal. In Fourier transform the abrupt changes in a signal produces huge harmonics (the reconstruction of such signal needs huge number of harmonics can be explained from Gibb's phenomenon) but in wavelet transform relatively large wavelet coefficients (in absolute value) are found around the discontinuity at all scales. If the oscillation of the signal is highly correlated with the oscillation of wavelet then the wavelet coefficients are found larger. The abrupt change in signal are visualized from *a*-*b* plot where the co-efficient are found distinct at all scale compared to smoother part of the signal but maxima and minima are visualized only at higher scale. Actually, the main feature of ECG and EEG signal are the rapid varying portion of the signal. Among several wavelets few are suitable for extraction of features of ECG or EEG. The following figures show the location maximum amplitude of co-efficient of CWT for ECG and EEG signal. The scalogram of ECG is the most distinct for the case of 'Mexican Hat' wavelet (since the oscillation of Mexican Hat wavelet has similarity with the varying part of the ECG signal at some scale). On the other hand, for the case of EEG the Meyer, Symlet8, Daubechies8 wavelets provides the most distinct scalogram. Above phenomena is visualized from Figure 5 and Figure 6.



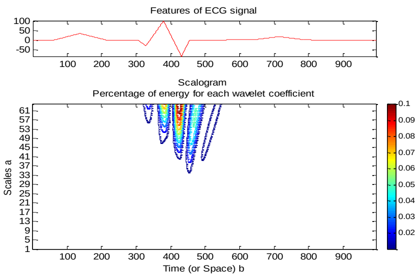
(a) Symlet4 (b) Symlet8



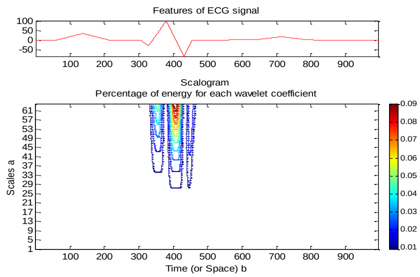
(c) Daubechies1



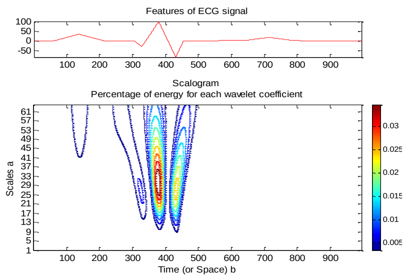
(d) Daubechies4



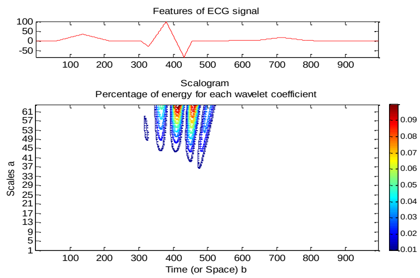
(e) Daubechies8



(f) Haar

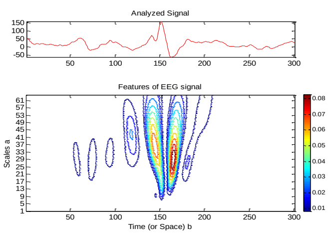


(g) Mexican hat

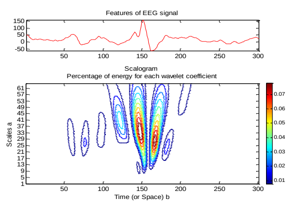


(h) Meyer

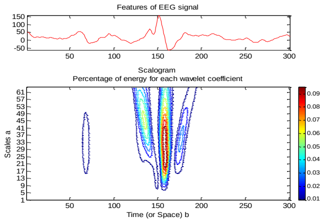
Figure 5: Scalogram of ECG signal



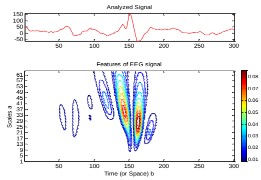
(a) Symlet4



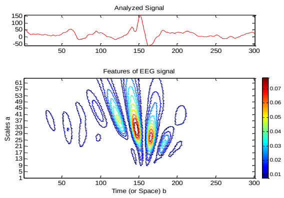
(b) Symlet8



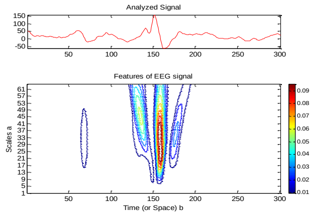
(c) Daubechies1



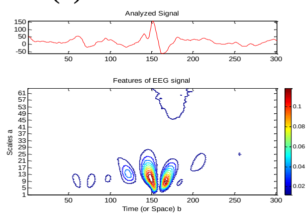
(d) Daubechies4



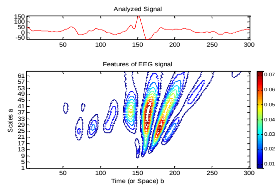
(e) Daubechies8



(f) Haar



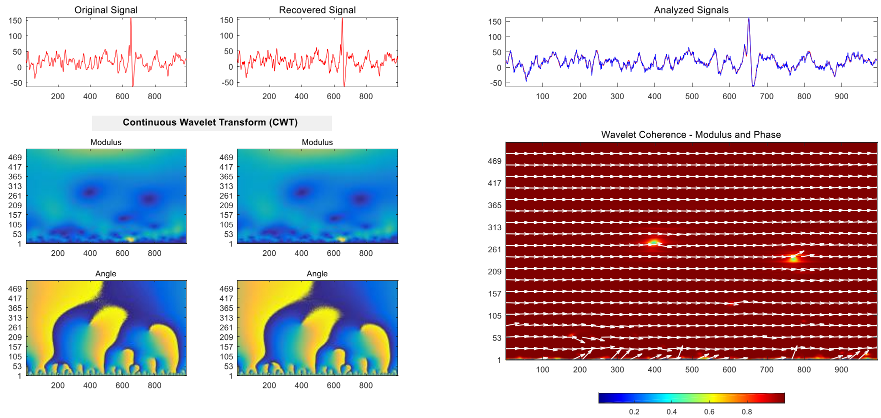
(g) Mexican hat



(h) Meyer

Figure 6: Scalogram of EEG signal

Figure 5 and 6 will be applicable to realize the condition of patient. Finally, the coherence of EEG signal is observed, using the CWT wavelet transform, as shown in Figure 7. Here *x*-axis is time (995 samples i.e. the length of *t*) and *y*-axis is scale (1 to 512), the arrow indicated the phase difference between original and recovered signal at different scale and time. At lower scale levels, little phase difference is found; but at upper scale, there is no phase difference visualized from Figure 7.



(a) Spectrogram of individual (b) Phase error

Figure 7: Coherence of original and recovered signal

Conclusions

One of the major applications of adaptive filter is to recover biomedical signal from its noisy or interfered version. The biomedical signals are highly sensitive to the noise, which creates huge difficulties for the responsible personnel to diagnose the condition of the patient perfectly. Thus, processing and enhancement of real time biomedical data is becoming more important to ensure error free diagnosis. In this paper de-noising of ECG and EEG signals using adaptive algorithm and the feature extraction using different wavelet transform are discussed. We can apply Kalman filter (which provides the same performance on the signals of any frequency) to recover ECG and EEG at the expense of processing time. We can use also use adaptive DWT to recover the signals. In future we will use Neural network for recovery and feature extraction of ECG and EEG where we need to train the system about the profile of both signals.

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