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EMD Based ECG Signal Denoising Techniques

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Abstract:
The electrocardiogram is the recording of the electrical potential of heart versus time. The analysis of ECG signal has great importance in the detection of cardiac abnormalities. The electrocardiographic signals are often contaminated by noise from diverse sources. Noises that commonly disturb the basic electrocardiogram are power line interference, instrumentation noise, external electromagnetic field interference, noise due to random body movements and respiration movements. These noises can be classified according to their frequency content. It is essential to reduce these disturbances in ECG signal to improve accuracy and reliability. Different types of algorithms are available to remove the noise from ECG signals. In this paper EMD, EEMD, CEEMD techniques have been proposed to remove the noise from ECG signals.

Keywords*:ECG, EMD, EEMD, CEEMD*

1. Introduction

Heart is a muscular organ,which pumps the blood throughout the body and collecting the blood circulating back from the body.When the electrical abnormalities of the heart occur then the heart cannot pump blood properly and supply enough to the body and brain.This can cause unconsciousness within second and death within minutes.ECG is a graphical recording of electrical impulses generated by heart,which is used to analyze heart diseases.ECG signals are oscillatory and periodic in nature.ECG is a non-stationary signal which is interfered by various types of noises, namely power line interference,electrode contact noise,motionartifact,baseline wander etc.,an ECG beat is shown in fig.

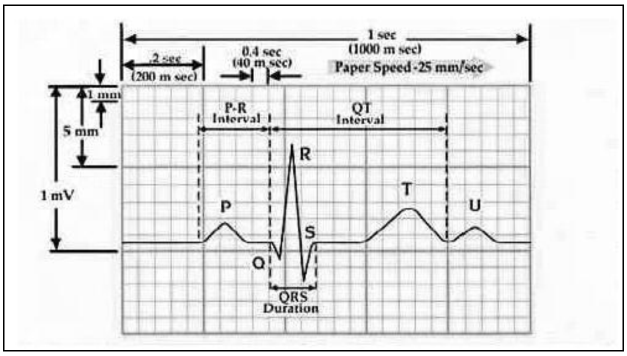

Figure1: Typical ECG Signal

A number of methods have been applied to de-noise ECG signals such as, digital filters, ICA, PCA, adaptive filtering, wavelet transform etc. The existing de-noising techniques have certain limitations. The filter bank based de-noising process smoothens the P and R amplitude of the ECG signal, and it is more sensitive to different levels of noise. The statistical model derived in PCA, ICA is not only fairly arbitrary but also extremely sensitive to small changes in either the signal or the noise unless the basis functions are trained on a global set of ECG beat types, moreover, the ICA doesn't allow the prior information about the signals for efficient filtering. Adaptive filtering requires reference signal information for the effective filtering process, and the reference signal has to be additionally recorded together with ECG. Wavelets need a basis function to be specified, moreover, the hard-thresholding WT leads to oscillation of the reconstructed ECG signal, and the soft-thresholding method reduce the amplitudes of the ECG waveform, especially reduce the amplitudes of the R-waves which is more important to diagnose the heart diseases.Therefore many researchers use Empirical Mode Decomposition (EMD) based denoisingtechnique.EMD also suffers from a problem called mode- mixing, which is overcome by EEMD and a good reconstructed signal comes from CEEMD
The rest of the paper is arranged as follows.The algorithms of EMD, EEMD,and CEEMD are presented in section 2.Simulation results to these methods are discussed in section 3 and finally we conclude in section 4.

2. ECG Denoising Methods

2.1. Empirical Mode Decomposition

Empirical mode decomposition (EMD) was introduced by Huang et al which is used to analyze non-linear and non-stationary signals such as ECG.EMD is used to investigate the chaotic nature of ECG signals.EMD decomposes a signal x(t) into a finite number of sub components called Intrinsic Mode Functions (IMFs). The IMFs represent the oscillatory mode of a particular signal and is obtained by a systematic process called sifting. To be considered as IMF,A signal must satisfy two conditions.

- The number of extrema and number of zero crossings must be equal or differalmost by one.
- At any point, the mean of the envelopes defined by the maxima and minima should be zero.

The decomposition procedure is termed as Sifting process and is described as follows.Letx (n) is given signal then

- Identify all local extrema in data x (n).
- Connect all local maxima by a cubic spline line as upper envelope and all local minima's as lower envelope.
- 3.In first sifting process the mean m_1 of upper and lower envelops is determined and subtracted from original data x(t) to obtain first component $d_1(t)$ as

$$h1 (n) = x (n) - m_1$$

If h_1 (n) satisfies the conditions to be an IMF,then it is considered as first IMF C_1 (n).

- Ifh_1 (n) not satisfies the conditions,then it is treated as data in 2^{nd} sifting process.Where steps 1, 2, 3 are repeated on h_1 (n) to derive second component h_2 (n) as

$$h_2 (n) = h_1 (n) - m_2$$

Where m_2 is the mean value determine from $h_1(n)$.If $h_2(n)$ satisfies conditions to be an IMF,then $h_2(n)= C_1(n)$.If it does not satisfies, standard difference(SD) is calculated from the two consecutive sifting results namely $h_{i-1}(n)$, $h_i(n)$ as

$$SD = \sum_{n=0}^{N} \frac{|hi-1[n]-hi[n]|2}{hi-1[n]2}$$

When the value of SD resides within predefined range (generally b/w 0.2 and 0.3), sifting process terminated and h_i (n) is termed as C_1 (n).

- OnceC$_1$ (t) is obtained; it is subtracted from the original data to get a residue r_1 (n).

$$r_1 (n) = x (n) - C_1 (n)$$

The residue $r_1(n)$ is treated as new signal,and sifting process as described above is carried out on $r_1(n)$ to obtain next residue $r_2(n)$.Therefore residue signal thus obtained can be expressed as

$$R_j(n)= r_{j-1}(n) - C_j(n)$$

This process is continues until the residue becomes a constant or monotonic function.To this end,for an L level decomposition the original signal can be represented as the sum of decomposed IMF's and resulting residues.

x (n) = (n)+ (n)

Like this the given signal is decomposed by using EMD method.Generally noise present in earlier IMF's.The IMF's in which noise dominates the signal is treated as noisy IMF's.In many of cases the noisy IMF's are discarded and remaining used for reconstruction .But due to this loss of information take place.So we will go in a different manner.Generally Spectral Flatness (SF) measure is used to determine the particular IMF is noisy IMF or not.Noisy IMF is identified by comparing SF of each IMF to a threshold value T (generally taken as 0.09).So the SF of IMF's which are grater than T,those are noisy IMF's.Spectral Flatness is calculated as ratio of geometric mean of power spectrum to it's arithmetic mean.

$$SF = \frac{\sqrt[L]{\prod_{n=0}^{L-1} H(n)}}{\frac{\sum_{n=0}^{L-1} H(n)}{L}}$$

Here we are applying noisy IMF's to filtering technique to remove the noise.Since significant part of high frequency content of ECG is in the range of 40-60 Hz, noisy IMF's are filtered using Butterworth filter of order 10 with cutoff frequency 60 Hz to extract significant signal components.This can be explained by the following diagram.

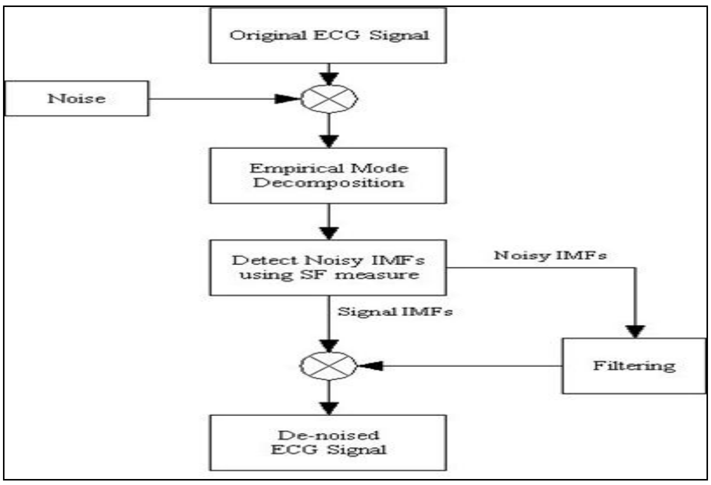

Figure 2: ECG Denoising Using EMD

2.2. Ensemble Empirical Mode of Decomposition

`EMD method suffers from a problem called Mode-mixing.i.e. presence of very disparate amplitude in a mode or presence of very similar oscillations in different modes.The mode mixing problem in EMD is described as

- IMF's contains signals of widely disparate scales or
- Signals of similar scales reside in different IMF components.

To overcome this problem we go for a new method called Ensemble Empirical Mode of Decomposition (EEMD).It performs the EMD over an ensemble of signal plus Gaussian white noise.The addition of Gaussian noise solves the mode mixing problem by populating the whole time-freq space to take advantage of dyadic filter bank behavior of EMD.EEMD defines true IMF components [ ]obtained via EMD over an ensemble of trials,generated by adding differentrealizations of white noise of finite variance to original signal x(n).Algorithm described as

- Generate $x^i[n]=x[n]+w^i[n]$,i=1,2,-----I,where$w^i[n]$ is different realizations of Gaussian noise.
- Each $x^i[n]$ is fully decomposed by EMD, getting their modes $IMF_K^i[n]$, where k=1, 2, ----K modes.
- Truekth mode of x (n) as is obtained as average of corresponding IMF_k^i.i.e

$$IMF\ (n) = \frac{1}{I}\sum_{i=1}^{I}\overline{IMF_k^i}\ (n)$$

2.3. Complete Ensemble Empirical Mode of Decomposition

To overcome mode mixing problem in EMD we came to EEMD.We overcome the problem of mode mixing but we have another one came into picture.The problem in EEMD is more number of iterations is required which makes the process robust.And also reconstructed signal includes residual noise.So we have new method called CEEMD,provides an exact reconstruction of original signal and better separation of modes with low computation cost.In this method first mode is obtained same way as in EEMD.Then compute first EMD mode over an ensemble of r_1 (n) plus different realizations of a given noise obtaining by averaging. HereE_j [.] operator provide j^{th} mode obtained by EMD.w^i is the white noise.The algorithm is as follows.

1. Decompose $(n) + \varepsilon_0 w_i(n)$by EMD I realizations to obtain first mode as

$$\overline{IMF_1}\ (n) = \frac{1}{I}\sum_{i=1}^{I}\overline{IMF_k^i}\ (n)$$

2. Calculate first residue as

$$r_1(n) = x(n) - \overline{IMF_1(n)}$$

3.Decompose$r_1(n) + \varepsilon_1 E_1\left(w^i(n)\right)$,where i=1, 2,--I realizations,until their first EMD mode define as second mode.

$$\overline{IMF_2}(n) = \frac{1}{I}\sum_{i=1}^{I}E_1\left(r_1(n) + \varepsilon_1 E_1\left(w^i(n)\right)\right)$$

Similarly

$$\overline{IMF_{K+1}}(n) = \frac{1}{I}\sum_{i=1}^{I}E_1\left(r_K(n) + \varepsilon_K E_K\left(w^i(n)\right)\right)$$

4. Continue this process until residue no longer feasible. Final residue

$$R(n) = x(n) - \sum_{k=1}^{K}\overline{IMF_k}$$

So the given signal can be expressed as

$$x(n) = R(n) + \sum_{k=1}^{K}\overline{IMF_k}$$

3. Results

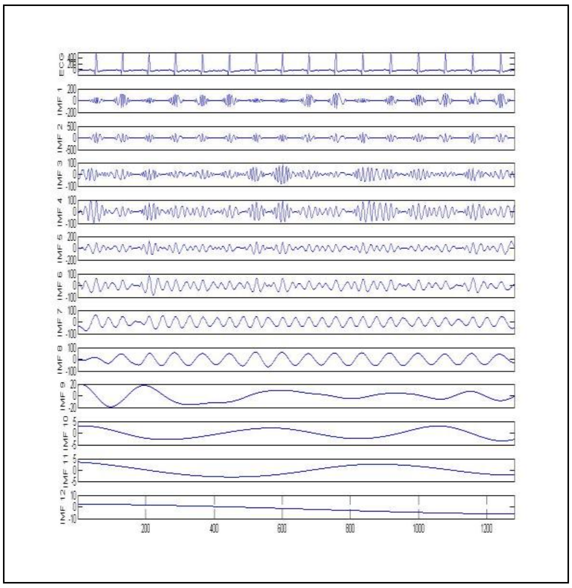

Figure 3: Decomposition of ECG signal by EMD

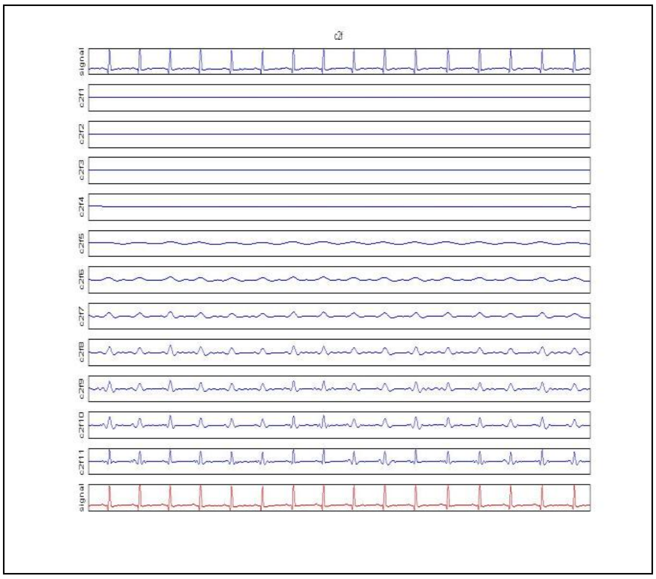

Figure 4: fine-coarse reconstruction of ECG Signal using EMD

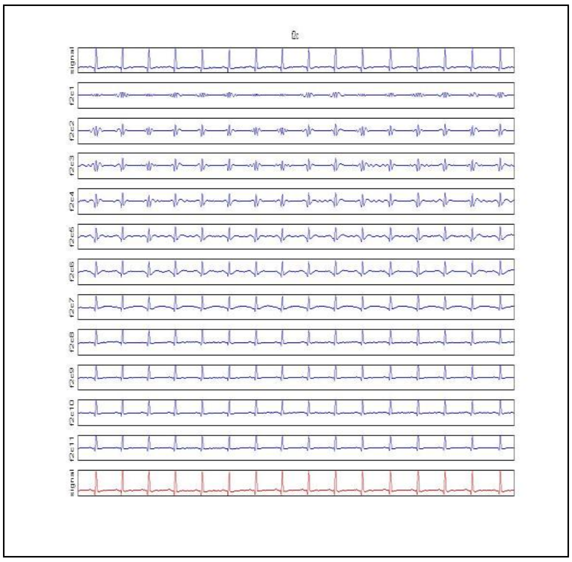

Figure 5: coarse-fine reconstruction of ECG Signal using EMD

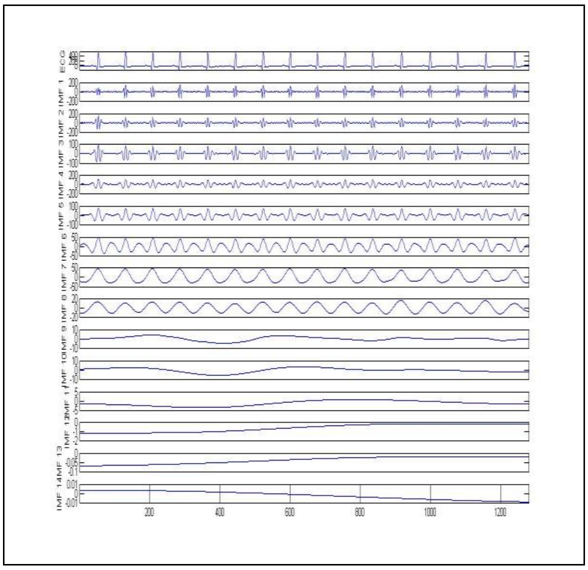

Figure 6: Decomposition of ECG signal by EEMD

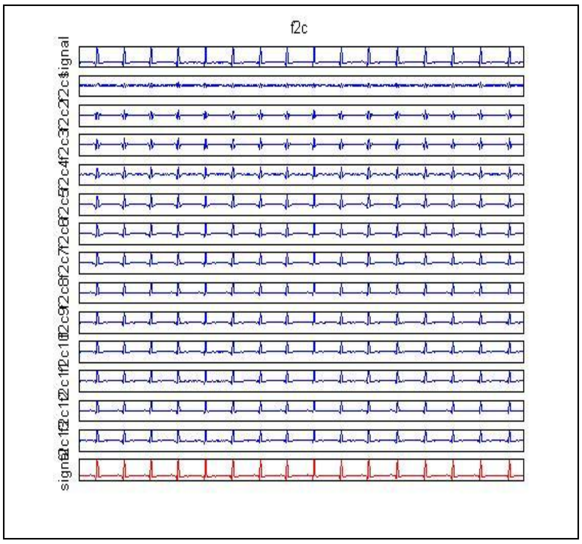

Figure 7: fine-coarse reconstruction of ECG Signal using EEMD

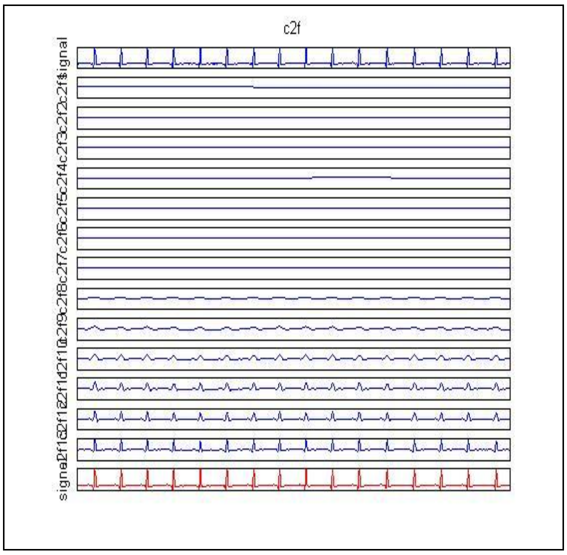

Figure 8: coarse-fine reconstruction of ECG Signal using EEMD

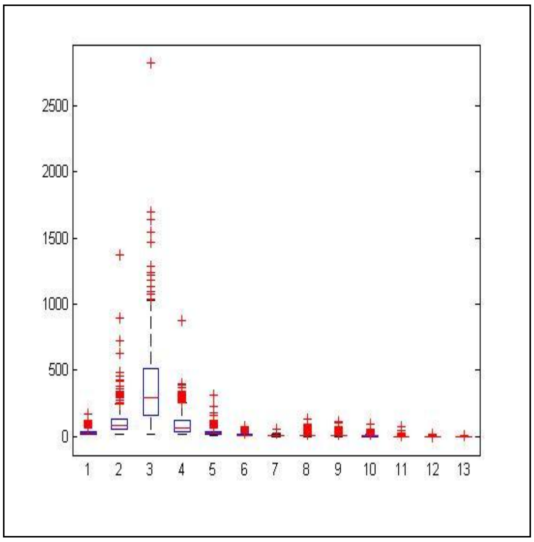

Figure 9: Box plots showing the sifting iterations for each mode of EEMD

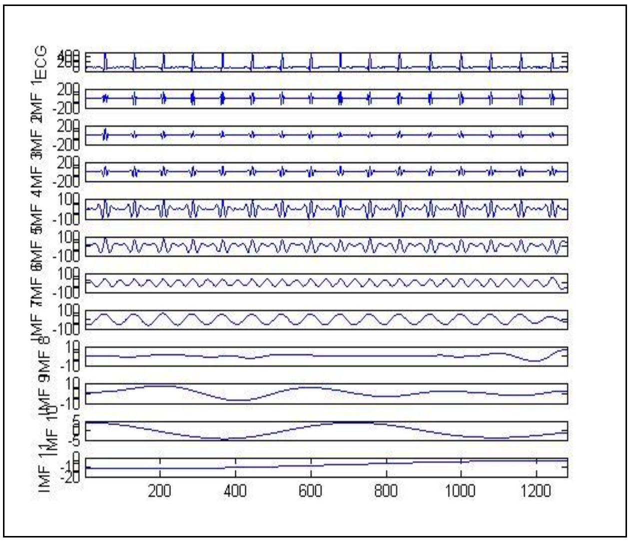

Figure 10: Decomposition of ECG signal by CEEMD

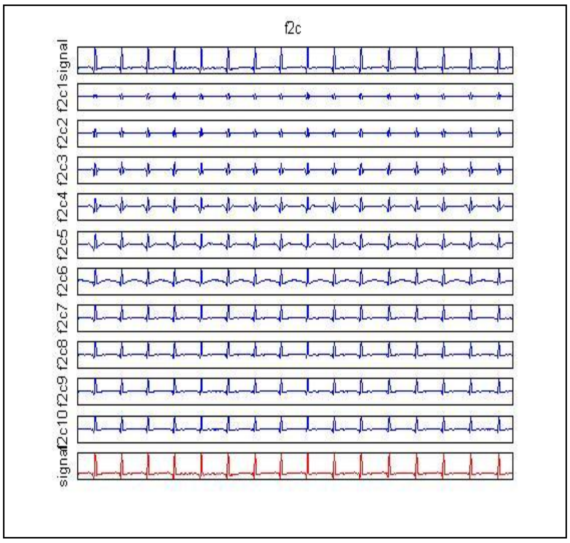

Figure 11: fine-coarse reconstruction of ECG Signal using CEEMD

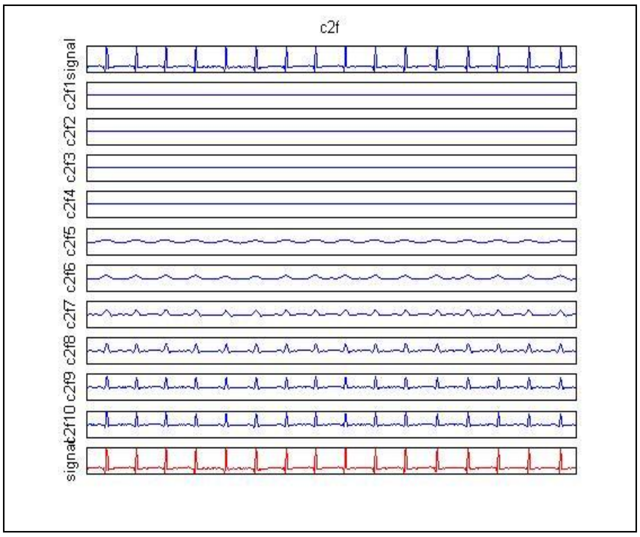

Figure 12: coarse-fine reconstruction of ECG Signal using CEEMD

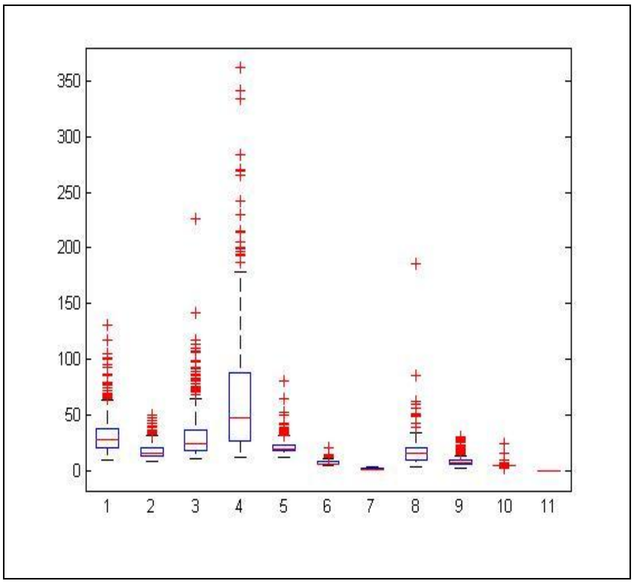

Figure 13: Box plots showing the siftingiterations for each mode of CEEMD

4. Conclusion

In this work we have present a new algorithm for removing noise from ECG signals. The proposed method has requires less sifting iteration to remove the noise from ECG signal compared to existing algorithms EMD, EEMD and thatthe original signal can be exactly reconstructed by summingthe modes.

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