Supervised Research Exposition Final Report

Noise and Artefact Removal from ECG using Variants of Empirical Mode Decomposition

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***Abstract*—Analysis of Electrocardiogram (ECG) signal is a popularly used method for diagnosis of heart diseases. For proper diagnosis, obtaining a good quality ECG signal is crucial. Unfortunately, ECG signal comes corrupted with many kinds of noises and artefacts in real life. Some major sources of artefacts are high frequency electromyographic (EMG) noise due to muscle contraction, low frequency baseline wander (BW) due to respiration of the patient, 50 Hz powerline interference, and motion artefacts due to movement of patient. Due to non-stationary and non-linear nature of the ECG signals, traditional bandpass filtering techniques are not very effective in removing these noise/artefacts. Among the various techniques that exist for ECG noise/artefact removal, I have focused on Empirical Mode Decomposition (EMD) technique and its more advanced versions. Experiments have been conducted on ECG data from the PhysioNet database in order to verify the effectiveness of these techniques.**

I. Introduction

Electrocardiogram (ECG) signal, which is the electrical activity of the heart muscles, has been used for diagnosis of heart diseases for over a century. ECG signal comes corrupted with many kinds of noises and artefacts in real life. Some major sources of artefacts are high frequency electromyographic (EMG) noise due to muscle contraction, low frequency baseline wander (BW) due to respiration of the patient, 50 Hz powerline interference, and motion artefacts due to movement of patient [1]. This work focuses on the EMG and BW noise, which are dominant in practice.

ECG signal is a non-stationary and non-linear signal. Hence, regular bandpass filtering methods, that are based on rejecting specific noise-frequency components, do not yield very good results. Therefore, techniques such as adaptive filtering, Wavelet based approaches and Empirical Mode Decomposition (EMD) [2] based methods are being used in the community. This work focusses on the EMD technique.

EMD decomposes a signal into basis functions called the Intrinsic Mode Functions (IMFs). But unlike Fourier Transform or Wavelet Transform, the basis functions are not decided a-priori but are obtained from the signal. The lower order IMFs contain the highly varying components of the signal and the higher order IMFs contain the slowly varying components. But there are issues with the basic EMD, mainly, the problem of “mode mixing”, where higher order IMFs contain some highly varying signal components as well and vice-versa. Hence, advanced versions of EMD need to be explored. These are EEMD [3] (Ensemble EMD), CEEMD [5] (Complementary EEMD), and CEEMDAN [6] (Complete EEMD with Adaptive Noise). Also, there is this issue that the QRS complex in the ECG signal contains high frequency components. Therefore, just removing lower order IMFs would cause distortion of the QRS complex. Another challenge is to accurately identify the IMFs that contain the noise/artefact components.

Many of the above mentioned challenges and their solutions are explored in [8], [7], [3], [4], [5], and [6]. Parts of them have been implemented in order to enhance different kinds of noise/artefacts and are presented in this report. This work combines the methods from several research papers in order to remove Baseline Wander and High frequency EMG noise.

This report is organized in the following sections as follows. Section II describes the theory of EMD, EEMD, and CEEMDAN. Sections III and IV describe how CEEMDAN is used, respectively, for BW correction and EMG noise removal. Section V presents the experiments done on ECG data from MIT-BIH database. Finally, sections VI and VII give conclusions and future work respectively.

II. Theory

A. Empirical Mode Decompostition (EMD)

This decomposition was first given by [2]. For any signal, performing an EMD decomposes the signal into Intrinsic Mode Functions (IMFs). IMFs are signals of the same length as the input signal and have the following properties. They have only one extremum between any two zero crossings and the envelope of the local maxima and that of the local minima are symmetric around zero. The signal is completely described as the sum of the IMFs and the residue. The lower order IMFs represent the rapidly varying signal components and the higher order IMFs represent the slowly varying components. Unlike Fourier transform and Wavelet transform, the signal decomposition does not rely on a predefined set of basis functions. Since EMD preserves varying frequency in time, it gives a proper representation for non-linear and non-stationary signals. The procedure to obtain the IMFs from a signal, called sifting, is described as follows.

For a signal $x(t)$, obtain the envelops of local maxima and local minima by cubic spline interpolation. Let $m_1(t)$ be the mean of these two envelops. $h_1(t) := x(t) - m_1(t)$. Now $h_1(t)$ is considered as the signal and $m_{11}(t)$ is found by taking the mean of the envelops of $h_1(t)$. This procedure is applied repetitively till the stopping criteria is reached. Sum of Difference (SD) is a stopping criteria.

$$SD = \sum_{t=0}^{T} \frac{|h_{1,k-1}(t) - h_{1,k}(t)|^2}{h_{1,k-1}(t)^2} \tag{1}$$

When SD is less than some threshold, we get the first IMF, $c_1(t)$. Now, the first residue $r_1(t) = x(t) - c_1(t)$, is subjected to the above procedure to obtain the second IMF, $c_2(t)$. This continues till we have obtained all the IMFs, $c_1(t), c_2(t), ..., c_N(t)$, and the final residue $r_N(t)$. The decomposition process stops when the final residue is either a monotonic function or has just one extremum. Thus, we decompose the signal as follows.

$$x(t) = \sum_{n=1}^{N} c_n(t) + r_N(t) \tag{2}$$

Problem of "Mode mixing" with EMD: The EMD, due to its local nature, may produce very highly-varying (high frequency) portions and slowly-varying portions of signal in the same IMF. Also, it may produce similarly varying signals in different IMFs. This is called "mode mixing". This is a major problem with ECG signals corrupted with motion artefacts, as artefacts are intermittent. To alleviate this problem, more advanced methods are required.

B. Ensemble EMD (EEMD)

Ensemble Empirical Mode Decomposition (EEMD) [3] technique first adds white Gaussian noise to the signal, then performs EMD to find the IMFs. Multiple versions of the IMFs are obtained by adding different noise realizations. Finally, the corresponding IMFs are averaged to obtain the final set of IMFs. This helps alleviate the mode mixing problem, as adding noise populates the signal, thus making the signal, not intermittent. Also, a large number of ensembles are averaged, hence, more or less canceling out the zero-mean Gaussian noise.

This creates two more problems that need to be addressed. First, in order to cancel out the noise in the final IMFs, we need a large number of ensembles. This increases computation time. Secondly, the different ensembles may have different number of IMFs, making it difficult to average over the corresponding IMFs. The first problem can be managed by Complementary EEMD (CEEMD) [4]. For every noise realization ensemble, a complementary noise (negative noise) is used to calculate another set of IMFs. But the second problem still remains.

C. Complete EEMD with Adaptive Noise (CEEMDAN)

Before going with the steps to obtain the IMFs, let us first get the notations out of the way. $E_k(.)$ denotes the operation to obtain the k^{th} IMF using EMD. $w^{(i)}(t)$ is the i^{th} realization of a zero-mean white Gaussian noise with unit variance.

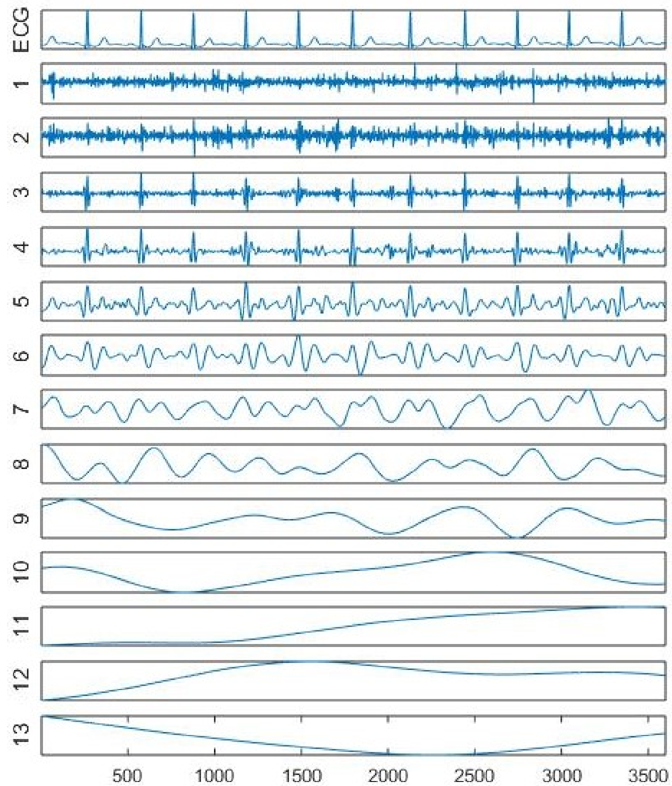

Fig. 1. CEEMDAN of an ECG signal. From top to bottom: ECG signal and its IMFs, numbered 1-13. The y-axes are not in the same scale for the subplots.

For each realization $x^{(i)}(t) = x(t) + \beta_0 w^{(i)}(t)$, calculate $E_1(x^{(i)}(t))$. The first CEEMDAN IMF, $d_1(t)$, is obtained by averaging over all the realizations. Now, the first residue, $r_1(t) = x(t) - d_1(t)$ is obtained. Now, calculate $E_1(r_1(t) + \beta_1 E_1(w^{(i)}))$ for each of the noise realizations and average over all the realizations to get the second IMF. Continuing with this procedure, the k^{th} IMF is obtained by averaging over all the realizations of $E_1(r_k(t) + \beta_k E_k(w^{(i)}(t)))$. As, in the case of the regular EMD, we stop when the last residue is either a monotonic function or has just one extremum. Fig. 1 shows the CEEMDAN IMFs for an ECG signal. We see that the oscillations increase with increase in IMF number.

Improved CEEMDAN [6] uses half of the noise realizations as the complement (negative) of the other half. For experiments, that are presented in this report, IMFs have been obtained using improved CEEMDAN.

III. Baseline Wander (BW) Correction

The procedure to correct for the BW has been taken from [7]. The BW signal is slowly varying signal. Hence, in the IMF decomposition, the higher order IMFs will have the BW information. If we remove some of the higher order IMFs and reconstruct the signal by summing the lower order IMFs, we get a BW-free signal.

$$\hat{x}(t) = \sum_{n=1}^{L} d_n(t) \tag{3}$$

Where $\hat{x}(t)$ is the reconstructed signal, $d_n(t)$ is the n^{th} IMF, L is the maximum IMF order which does not have any BW components. All that remains now is to find L. A good way to quantify the oscillations of an IMF is to look at the Zero Crossing Rate (ZCR), as IMFs are non-stationary signals. For practical ECG signals, it is observed that all IMF with ZCR less than 1.5 can be discarded while reconstruction. We calculate ZCR for IMFs starting from the last IMF and L is the obtained as the first IMF (from the end) such that $ZCR(d_L(t)) < 1.5$.

IV. High Frequency (HF) EMG noise removal

The procedure to remove HF EMG noise has been taken from [8]. In the original paper, they obtained the IMFs using the traditional EMD. We have used CEEMDAN instead. This method assumes that the positions of the R peaks are known beforehand. The procedure has four parts.

1) Obtaining R positions.
2) Extraction of QRS complex and proper windowing.
3) Use t-test to obtain the IMFs that contribute to noise.
4) Partial reconstruction of signal.

A. Obtaining R positions

The procedure that we have used to obtain R positions is inspired from, but is not identical to what is mentioned in [1], as an amplitude and first derivative approach. First, an amplitude threshold is chosen as $Th_A = 0.4 \times \max(x(t))$ in a $10s$ long signal $x(t)$, and the signal is clipped to Th_A if $x(t) > Th_A$. Now, the difference signal $x'(t) = x(t+1) - x(t)$ is obtained. Here, t are integers. Derivative threshold, $Th_d = 7.2/F_s$ is chosen. F_s is the sampling frequency of the ECG signal. If $x'(t_i) > Th_d$ and $x'(t_i + 1) > Th_d$, then we mark t_i as the onset of an R peak. Now, we don't check for another onset in the interval I_i from time t to $t+120ms$. This is because, the QRS complex is at most $120ms$ in duration. The R position in I_i is obtained as the position where $x(t)$ is maximum in the interval I_i. We run this algorithm over the entire signal to find all R positions.

B. QRS Extraction and Windowing

Since the QRS complex has high frequency components, the first three IMFs, summed to obtain $b(t)$ is used to extract it. Starting from an R position, the onset of Q is obtained as the first zero-crossing to the left of the first local minimum from R. The offset of S is obtained as the first zero-crossing to the right of the first local minimum from R.

Once, these positions are obtained, a Tukey window is applied to the QRS complexes. Let $2T$ be the flat region width of the Tukey window and τ be the one-side transition region width, then we define $\beta = \frac{\tau}{2T}$. $\beta = 0.3$ is chosen for the first IMF. For the j^{th} IMF, $\beta = j \times 0.3$ is set. The window spreads with higher order IMFs, as they contain less amount of HF noise.

C. Determine noise IMF numbers by t-test

It is a valid assumption that the additive HF noise has zero mean. Now, $C_{PS}^{M}(t)$ is obtained by partially summing the first M IMFs. Assuming ergodicity of the noise process, we set the null hypothesis for the Student's t-test as $H_0 : mean(C_{PS}^{M}(t)) = 0$ and alternative hypothesis $H_1 : mean(C_{PS}^{M}(t)) \neq 0$. Let t be the t-distribution with $n-1$ degrees of freedom, where n is the ECG signal length.

$$p - value = \mathrm{P}(|t| > |\frac{\bar{X}}{s/\sqrt{n}}|) \tag{4}$$

Where $X = C_{PS}^{M}(t)$ and s is the standard deviation of X. A significance level α is chosen and the null hypothesis is rejected if the p value is less than $alpha$. The noise order P, which is the maximum IMF number, for which the null hypothesis is not rejected, is determined.

D. Partial Reconstruction of Signal

Let $\psi_i(t)$ be the signal corresponding to the i^{th} IMF with support only at the Tukey-windowed QRS complexes. Let $\bar{\psi_i}(t) = 1 - \psi_i(t)$ be the complement window signal. Then the reconstructed signal is given as follows.

$$\hat{x}(t) = \sum_{i=1}^{P} \psi_i(t) d_i(t) + \sum_{i=1}^{P} a_i \psi_i(t) d_i(t) + \sum_{i=P+1}^{N} d_i(t) + r_N(t) \tag{5}$$

Here, $d_i(t)$ is the i^{th} IMF, P is the noise order, N is the total number of IMFs, a_i is a small fraction (chosen as 0.1 in our experiments). A non-zero a_i ensures that some small amount of noise is preserved in the lower order IMFs, preventing kinks at the QRS complex interfaces.

V. Experiments

A. BW Correction

We take the signal no. 16272 from the MIT-BIH Normal Sinus Rhythm Database [10]. This signal is chosen, as this is a fairly noise-free signal. Now, we add an artificial BW as follows.

$$B_w(t) = 50\sin(\pi t) + 40\cos(0.6\pi t) + 20\cos(0.2\pi t) \tag{6}$$

We use the improved CEEMDAN to obtain the IMFs, with number of ensembles $= 80$ and noise variance is such that SNR $= 5$ (linear scale) and follow the procedure in section III. The SNR (linear scale) obtained after BW correction was 8.95 which compares well with SNR $= 9.29$ in [7]. Fig.2 shows the results of the BW correction for 16272 signal from the MIT-BIH Normal Sinus Rhythm Databse [10].

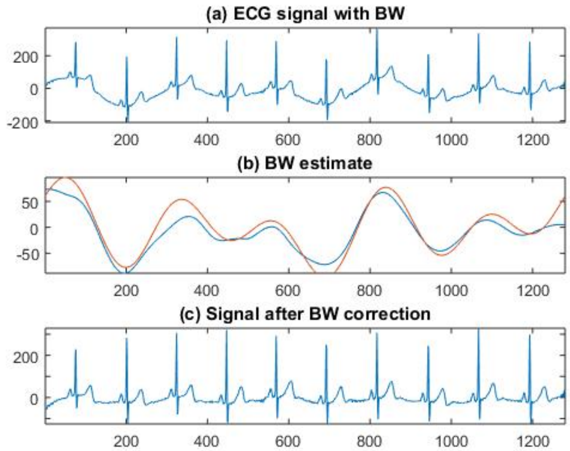

Fig. 2. BW correction results for the 16272 signal from the MIT-BIH Normal Sinus Rhythm Databse. (a) Signal corrupted with BW. (b) The blue plot is the estimated BW and the red plot is actual BW. (c) Signal after BW correction.

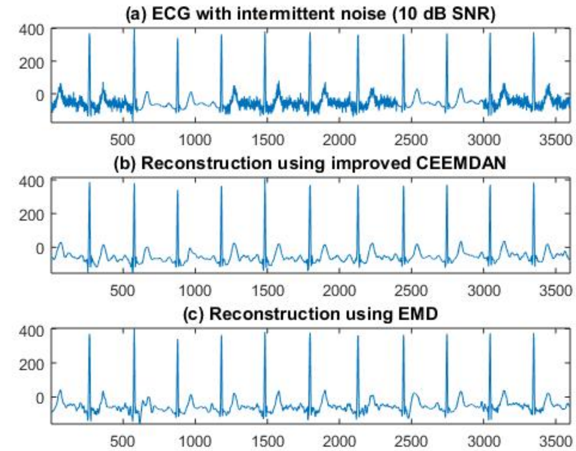

Fig. 3. Comparison of HF noise removal results for EMD method and improved CEEMDAN method for obtaining IMFs. (a) Signal corrupted with intermittent AWGN. (b) Reconstructed signal for CEEMDAN. (c) Reconstructed signal for EMD.

TABLE I
SER VALUES FOR DIFFERENT NOISE LEVELS

SNR (in dB)	SER (in dB)
6	8.12
10	12.04
11.76 (intermittent noise)	13.87 (using CEEMDAN) 13.67 (using EMD)
14	16.01

B. High Frequency Noise Removal (EMG Noise)

The ECG signal used for this experiment is the first lead of record 103 from the MIT-BIH arrhythmia database [10]. A white Gaussian noise is added intermittently to the signal. To calculate the IMFs using the improved CEEMDAN method, number of ensembles $= 80$ and noise variance is such that SNR$=$ 10dB. For the t-test, $\alpha = 0.01$ is chosen. For quantifying the output, we calculate the SER (Signal to Error Ratio) as below.

$$SER = \frac{\sum_t x^2(t)}{\sum_t [x(t) - \hat{x}(t)]^2} \tag{7}$$

Where $x(t)$ is the uncorrupted signal, and $\hat{x}(t)$ is the reconstructed signal.

First, we add an intermittent white Gaussian noise (WGN) to the signal such that SNR= 11.76dB. We see in table I, that for the improved CEEMDAN method for obtaining IMFs, we get better SER than the EMD method. This is because of mode mixing problem with the regular EMD. We can also see the difference in Fig.3. Now, we add WGN to the whole signal with different noise levels and use the improved CEEMDAN method to obtain IMFs. The results are summarized in table I.

Discussion: There are too many parameters for HF noise removal, in the method described above. Hence, the method needs to be made more adaptable to be used in a clinical setting. However, the method to extract the QRS complex using CEEMDAN is very robust, as seen experimentally. Extraction of QRS complex is an important part even in other methods for ECG noise/artefact removal, e.g., using Wavelet Decomposition. We can use the method involving CEEMDAN first, to extract the QRS complex; then other methods can also be utilized to process the ECG signal further.

VI. CONCLUSION

This report describes methods based on improved Complete Ensemble Empirical Decomposition with Adaptive Noise (CEEMDAN), to remove two kinds of corruptions to ECG signals, namely, Baseline Wander (BW) and high-frequency EMG noise. CEEMDAN is an improvement upon EMD, taking care of the mode mixing problem. The experiments are done on ECG signals taken from MIT-BIH database with added synthetic noise and BW. We see that methods based on CEEMDAN, can effectively de-noise ECG signals, which are non-linear and non-stationary signals. Moreover, extraction of the QRS complex is one of the best things about the CEEMDAN approach. The extracted QRS complex can be used, along with other ECG de-noising techniques, to get rid of noise/artefacts from ECG.

VII. FUTURE WORK

The experiments performed, as described in this report, are done separately for high frequency noise removal and Baseline Wander correction. Also, the noise and BW signal are constructed synthetically. We plan to test the techniques on composite noise (mixture of BW and EMG noise). Also, we need to test their performance on real noise.

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