Removal of Baseline Wander from ECG using CEEMD and Adaptive Morphogocial Function

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ABSTRACT

ECG is a documentation of the electrical activities of the heart and it is used for the identification of a number of cardiac imperfections. Quite ECG signal get tainted by various kinds of artifacts, thus in order to gain proper information from them they must first be denoised. Baseline wander is one of the most common artifact in ECG. CEEMD shows better denoising performance compared to EMD and EEMD. Results also prove that morphology of an ECG signal drastically improved by using adaptive SE in morphological functions. Proposed method presents a novel approach for the filtering of baseline wander artifact of ECG by using a cascade of CEEMD and morphological functions using adaptive structuring elements. By using this novel approach for denoising of baseline wander artifact, it is ensured that the morphological information present in the ECG signal remains preserved and denoising performance is independent of heart rate and external factors. Proposed method is compared with all latest methods and results prove that proposed method provide far superior denoising and morphological results in terms of output Minimum Square Error, Output Signal to Noise Ratio and Correlation Coefficient.

KEY WORDS: ECG, Morphological Operators, EMD, EEMD, CEEMD, Baseline Wander.

1. INTRODUCTION

ECG signal is a quasi-periodic signal quantifying the electrical activities of the heart. It includes information content mostly in the 0.5-120 Hz range and is used to ascertain if a patient is suffering from any form of cardiac disorder. It primarily consists of the P wave, QRS complex and the ST segment. Any additional structures present in the ECG signify noise or cardiac defects. The diagnosis of these defects is generally performed by presence of certain morphologies in the ECG signal. Thus the morphology of an ECG signal is a crucial aspect which must not be tampered with to as large an extent as possible. However, ECG signal also captures a large amount of varying noises as well, thereby making proper diagnosis very difficult. Hence for proper diagnosis a filtering process is required to remove the constituent noise while ensuring no loss of information in terms of the morphology of the ECG signal. Baseline wander artifact is one of the most important types of noises present in ECG and it present in middle frequency region of ECG. It takes place due to the respiration of the patient, thereby making it omnipresent in all ECG signals. This artifact is often found during stress ECG in particular as patient breathing rate increases. The baseline wanders artifact result in a gradual sloping of the ST segment and a reduced R-R duration in the ECG signal. All these changes in the morphology are natural and necessary for diagnosis, however most existing denoising methods generally tend to a loss of information due to filtering. In this paper, a new technique is proposed to remove baseline wander from ECG signals by cascading of Complete Ensemble Empirical Mode Decomposition (CEEMD) and morphological operators with adaptive structuring elements (SE). The main contributions of the paper are as follows:

a) The cascading helps in overcoming inherent weaknesses that exist in using either method alone.

b) Each method preserves shape, thus a cascade of these two methods results in a strong preservation of shape of signal.

c) Further the lengths of structuring element are derived from real time ECG signal, thus making proposed filter adaptive to changes in heart rate and consequently changes of lengths of QRS and ST complexes.

This paper is divided into six sections, Section-II covers literature survey. Section-III explains background of proposed method. Proposed method is covered in Section-IV. Section-V shows the results obtained and Section-VI, follow by reference, is a summary of conclusions.

Literature Survey: Initial techniques of baseline wander denoising from ECG signals has used digital window based filters for the removal of low frequency noise from ECG but these filters introduced ripples in pass band if a sharp cut-off is opted and these ripples cause changes in the morphology of the ECG signal, which is unacceptable from a diagnosis point of view. Furthermore, inability to effectively use of Fourier Transform (FT) on ECG signal due to its non-stationary and non-linear property, implies uncertainty about exact frequency cut-offs requirement of window based filters. As an improvement upon window based filters, adaptive filters (LMS, NLMS, BLMS, etc.) were used. These filters involve dynamic tracking of the signal and estimation of noise based on difference between the tracked signal and the observed one. The problems that arise while using these filters for ECG denoising begin with requirement of pure input samples to obtain an estimate of the way the signal changes. Further issues arise due to the mean square error criterion for adaptive filters and also the fact that the reference signals are not correlated very well with the primary input. Thus even though these filters improve performance compared to simple window based filtering but there remained considerable scope for further improvement.

Recent advancements in non-linear signal analysis using wavelets have led to the extensive use of wavelets in ECG denoising. The work initially proposed by Donoho (1995), was carried forward to the field of ECG denoising and many algorithms have been built over it. Traditional wavelet approach has been found to be ineffective for the removal of baseline wander noise as confirmed by Luong (2013). To address this issue a fuzzy rule based multi wavelet technique was proposed by Ho (2008), which helped in terms of optimization of pre and post filtering choices for a particular data set.

Huang (1998), proposed a new technique, known as Empirical Mode decomposition (EMD) for analysis of non-linear non-stationary signals. This has been found to be very effective in ECG denoising and has been extensively used in several algorithms. However, most of the work using EMD has been done in relation to the removal of high frequency noises. Denoising of ECG signal using linear filtering especially Butterworth Low pass filter, gives better results when compare to direct denoising by EMD method. When EMD combined with adaptive filters, it gives better results compared to its combination with linear filters. A combination of EMD and wavelets is a very effective technique for ECG denoising. Further improvements are made upon this by Zhang (2010). In this work, he analyzes the energy of each IMF and accordingly detects the noisy IMF's and thus only the noisy IMF's are denoised using the wavelet based soft thresholding technique. All these techniques are generally applied to deal with the lower IMF's or high frequency components present in the signal and hence can't be used to deal with baseline wander.

EMD was first used in the paper by Zhi and Yu (2006), for the denoising of baseline wander. The residue signal was assumed to be an estimate of the baseline wander and this residue was removed to correct the noise signal. Further work in this field was done by Na Pan (2007). The signal was decomposed into 15 IMF's and it was considered that the last three IMF's contained mostly noise components so the baseline wander was removed by removal of last three components. The problems that arose with these works were the limited nature of tested signal and the lack of a proper system to find out number of noise effected IMFs. The major drawbacks present in EMD are its sensitivity to noise and the property of mode mixing which introduces error in the taken signal. Hence to overcome these Huang proposed a system of Ensemble Empirical Mode Decomposition (EEMD) and this was improved upon for denoising of ECG however EEMD also faced most of the same problems of EMD in terms of insufficient denoising strength on its own.

The use of Morphological operators has wide applications in image processing. Chee-Hung (1989), used morphological operators first time for denoising of biomedical signals. Building on this work, OGUZ (1992), in his paper title "A morphology based algorithm for baseline wander elimination in ECG records" used an opening operation followed by closing. The opening operations was used to extract the positive pulses such as P, R, T and U waves while the closing operation was used to remove the negative waves such as S wave. The primary drawback with this approach was the use of an ECG like but not pure ECG signal for analysis. Further the use of a disk shaped structuring element (SE) was a poor approximation for a real ECG. In another paper by Sun (2003), neonatal ECG signals were picked up for analysis. The aim of this paper was to successfully preserve the QT interval present. Opening and closing operations were used in tandem and then averaged to remove the QRS complex and leave with the QT complex. This was then fed as the structuring element for the second stage of morphological filtering. This work, while addressing the drawbacks of previous works, aims at the study of neonatal ECG signals only and need to be generalized.

A more recent approach was outlined by Zhongguo Liu (2011), here the morphologies present in the ECG signals were removed in two steps by using opening and closing operations in tandem and then taking the average. First the QRS complex is removed and then the P and T pulses are removed. Linear structuring elements are used in accordance with the available biological data. The major limitation being here that the ECG being a quasi-periodic and dynamic signal, the pulse widths are not fixed and keep on varying, hence a more adaptive structuring element are required. This problem is especially observed in the case of stress ECG's, where there is an inherent baseline drift, an upward slope in the ST interval and a clear change in the lengths of the QRS and ST segments. The major advantages however lie in the computational simplicity present in the use of morphological operators, further the ability of these operators to retain morphological information present in the signal is crucial.

It was found that EMD and Morphological functions alone has limited ECG denoising capacity so Mahipal (2016), proposed a new method for ECG baseline denoising by combining EMD with morphological functions to fetch optimum results. It is observed by them that performance of baseline denoising from ECG can be improved by using EEMD in place of EMD and by using adaptive SE for morphological operators.

Back ground:

Complete Ensemble Empirical Mode Decomposition: EMD is a method of analyzing non-linear and non-stationary signals and it is a fully adaptive and data driven technique. However, it experiences some problems such as the presence of oscillations of very dissimilar amplitude in a mode or the presence of very similar oscillations in different modes; this is known as "mode-mixing". To overcome mode mixing issues, a new method, known as Ensemble Empirical Mode Decomposition (EEMD). In EEMD, an ensemble of the original signal is taken by adding various instances of Gaussian white noise to it. These instances are then broken down using EMD and the average over the entire ensemble is taken. Problem of mode mixing and oscillations is solved by averaging of IMFs. However EEMD also has a few problems of its own like it is computationally very expensive and due to uneven number of modes over all the ensemble, the final amplitudes associated with the IMF's is greatly reduced. Thus a more advanced technique known as Complete Ensemble Empirical Mode Decomposition (CEEMD) is used for decomposition of ECG into IMFs. In CEEMD, breakup of a signal into its constituent IMFs is performed in following manner:

a) Using EMD, decompose K realizations ($x[n] + \varepsilon w^k[n]$) of the base signal plus added white Gaussian noise to obtain their first modes and thereby create an ensemble of first IMFs by average over to obtain first true IMF using following formula

$$\widetilde{IMF_1}[n] = \frac{1}{K}\sum_{k=1}^{K} IMF_1^k \qquad (1)$$

b) At the first stage, the first residue is calculated by

$$r_1[n] = x[n] - \widetilde{IMF_1}[n] \qquad (2)$$

c) For the second stage of CEEMD, this residue signal is consider as base signal and create an ensemble of k realizations of the residue with Gaussian white noise, the first IMF for each element is obtained and averaged over to return second true IMF, which is written as

$$\widetilde{IMF_2}[n] = \frac{1}{K}\sum_{k=1}^{K} E_1\left(r_1(n) + \varepsilon_1 E_1\left(w^k[n]\right)\right) \qquad (3)$$

d) Similar to above mentioned equation now calculate second residue. This will then form the basis for the third true IMF.

e) Continue the above mentioned steps until further decomposition is no longer possible.

f) Subtract all the obtained true IMF's to obtain the final residue.

Initial ECG signal can be considered as sum of the true IMF's and the remaining residue. Initial ECG signal is given by

$$x(n) = \sum_{i=1}^{N} c_i(n) + d \qquad (4)$$

CEEMD results in much improved computational complexity and a reduced ensemble size, further the low mode amplitude problem is not experienced due to the fact that only first mode is searched at each realization of this method. This method guarantees almost zero reconstruction error. This is very important feature of this method, which ensures that no information is lost while working with biological signals such as ECG and it prove superiority of CEEMD over EMD and EEMD for removal of baseline wander from ECG. Results also prove same conclusion regarding CEEMD.

Adaptive Morphological Operators: Mathematical morphology is a powerful process for the numerical analysis of geometric structures. It consists of numerous algorithms designed to obtain information concerning shape and size from a geometric object. Selected Structuring Element (SE) is the most important feature of these filters and by varying the shape and size of the SE, it enables to obtain information from the non-linear signal. Erosion and Dilation are the fundamental morphological operators upon which the more advanced processes and filtering techniques are based. They are

Erosion: It is used to find matches of a SE in the signal under consideration and defined as

$$f \oplus l(n) = max\left(f(n-i) + g(i)\right) \qquad (5)$$

Dilation: It is generally used to fill small pits in the signal and perform smoothing and defined as

$$f\theta l(n) = \min\left(f(n+i) - g(i)\right) \qquad (6)$$

Two important operations known as opening and closing, derived from the erosion and dilation operators, are used in proposed method and they are defined as

$$\text{Opening: } (f^\circ l)(n) = (f\theta l \oplus l)(n) \qquad (7)$$

$$\text{Closing: } (f \cdot l)(n) = (f \oplus l\theta l)(n) \qquad (8)$$

Opening operation is responsible for the removal of peaks and smoothening of the contour. Closing handles removal of pits and discontinuities.

2. PROPOSED METHOD

The algorithm consists of passing the noisy signal through cascaded CEEMD and adaptive morphological filters and has following steps:-

a) Decomposition of Noisy ECG signal into constituent IMFs using CEEMD.

b) Dropping of artifactual IMFs and partial reconstruction of ECG signal for partial denoising.

c) Extraction of lengths of QRS complex and ST segment.

d) First phase of morphological filtering using QRS complex length as length of SE.

e) Second phase of morphological filtering using ST segment length as length of SE.

f) Subtraction of the remaining residual signal from partially denoised signal obtained in Step 2.

g) Calculation of performance parameters (SNR, MSE and correlation) from the output signal.

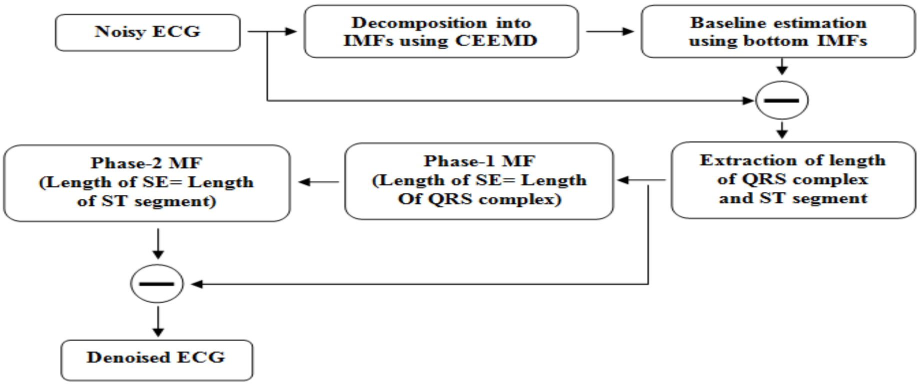

Fig.1. Proposed Methodology

Step 1: Noisy ECG is decomposed into N true IMFs using CEEMD operation

$$x_{original}(n) = \sum_{i=1}^{N} c_i(n) + d \qquad (9)$$

Step 2: To perform partial filtering, a set of IMFs is chosen to drop. Based on experimental data, the value of lower IMFs (m) to be discarded is obtained as

$$m = round(0.38\,N) \qquad (10)$$

This number is obtained by testing real time ECG signals with known noise added to them. Various fractions of the total number of modes are dropped and it is observed that on an average, maximum SNR and correlation are obtained using 0.38. Thus, the CEEMD filtered ECG signal is given as

$$\overline{x}_{ceemd}(n) = \sum_{i=1}^{N-m} c_i(n) \qquad (11)$$

This is partially filtered ECG signal. The aim behind partially filtering it is to ensure that no shape related information is lost.

Step 3: The morphological filters have been divided into two steps, one to remove QRS complex and other to remove ST wave. This is done because if all the features are removed at once, it may give rise to severe distortion and loss of information. Linear SEs are used because they are found to be more accurate for denoising ECG signals. A simple artifact analysis algorithm using a wavelet breakdown and identification of ECG components, is used to determine the lengths of the complexes and hence the structuring elements. It is a fully adaptive method in which position of peaks is located and then average length of complexes is obtained based on the number of samples between peaks. The length of the QRS complex is defined as the number of samples between the onset of the Q wave and the onset of the S wave. By obtaining the locations of S and T peaks, length of ST interval is calculated.

Step 4: The partially filtered ECG signal is now applied to the first morphological filter. Based on the length of a QRS complex obtained from the real time ECG signal as mentioned earlier, a linear structuring elements (SE1) of length '$l1$'is used. QRS complex removed ECG signal is given by

$$\bar{x}_{mp1}(n) = \{(\bar{x}_{ceemd}{\circ}l1 \cdot l1)(n) + (\bar{x}_{ceemd} \cdot l1{\circ}l1)(n)\}/2 \qquad (12)$$

Step 5: The QRS complex removed ECG signal is then applied to a second morphological function to remove the ST wave. ST interval of partially filtered ECG signal is used as length of structuring elements for second morphological filter, '$l2$'. ST segment removed ECG signal is given

$$\bar{x}_{mp2}(n) = \left\{\left(\bar{x}_{mp1}{\circ}l2 \cdot l2\right)(n) + \left(\bar{x}_{mp1} \cdot l2{\circ}l2\right)(n)\right\}/2 \qquad (13)$$

This signal does not contain any of the characteristic ECG segments. It is an estimate of the total remaining baseline noise present in the original signal.

Step 6: This obtained noise signal is subtracted from the initially denoised ECG signal to achieve the clean or denoised ECG signal, which is given by

$$x_{denoised}(n) = \bar{x}_{ceemd}(n) - \bar{x}_{mp2}(n) \qquad (14)$$

Step 7: For clean ECG output signal, performance parameters are calculated as

(i) Output Mean Square Error, $MSE = \Sigma\left(x_{original} - x_{denoised}\right)^2$ (15)

(ii) Output Signal to Noise Ratio, SNR (dB) $= 10 * \log \frac{X_{original}^2}{\left(X_{original} - X_{denoised}\right)^2}$ (16)

To compare performance of proposed method, same process is carried out for testing using various combinations of cascading using EMD and EEMD also and also all three types of morphological operators, static, partially adaptive and fully adaptive.

3. RESULTS

X-axis shows number of samples and Y-axis shows amplitude of signal. Table.1 shows corresponding results of ECG baseline wander denoising method using EMD, EEMD and CEEMD.

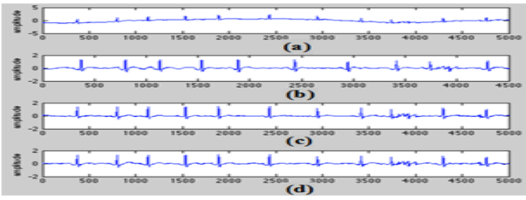

Fig.2 (a) Noisy signal (b) Denoised signal using EMD (c) Denoised signal using EEMD (d) Denoised signal using CEEMD

Table.1. Comparision of CEEMD with EMD and EEMD

Parameter	Method		
	EMD	EEMD	CEEMD
Output MSE	0.0023	0.0020	0.0018
Output SNR (Db)	24.5055	28.2483	30.3593
Correlation Coefficient	0.8825	0.9153	0.9374

(Input SNR =-16.2870 dB; Input MSE = 0.4096)

Fig.3 shows corresponding plots of denoised ECG using morphological functions with various levels of adaptiveness. X-axis shows number of samples and Y-axis shows amplitude of signal. The table.2 shows corresponding results with various levels of adaptiveness of morphological functions for ECG baseline wander denoising.

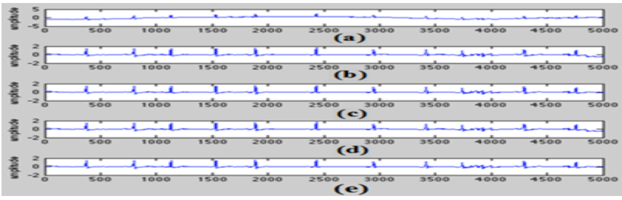

Fig.3 (a) Noisy Signal (b) Denoised signal using static morphological operators (c) Denoised signal using QRS adaptive morphological operators (d) Denoised signal using ST adaptive morphological operators (e) Denoised signal using fully adaptive morphological operators

Table.2. Comparision between different types of morphological functions (MF)

Parameter	Method			
	Case 1	Case 2	Case 3	Case 4
Output MSE	0.0027	0.0024	0.0024	0.0022
Output SNR (Db)	20.8442	23.5292	22.7893	25.6805
Correlation Coefficient	0.8732	0.9027	0.8983	0.9184

(Input SNR = -16.2870 Db; Input MSE = 0.4096)

Case 1: Static MF (SE1= 0.11Fs; SE2= 0.3 Fs)
Case 2: Partially Adaptable MF-1 (SE1 = QRS Interval; SE2 = 0.3 Fs)
Case 3: Partially Adaptable MF-2 (SE1 = 0.11Fs; SE2 = ST Segment)
Case 4: Fully Adaptable MF (SE1= QRS Interval; SE2 = ST Segment)

The filtering properties change as move from a static function, to one in which the first stage is adaptive, then one in which the second stage is adaptive and finally the fully adaptive model. As can be clearly seen, adaptability enhances the denoising property of filter with the fully adaptive filter giving the best results.

Fig.4 shows plots of denoised ECG using different cascaded combination. X-axis shows number of samples and Y-axis shows amplitude of signal. Table.3 shows corresponding results of different cascaded combinations for ECG baseline wander denoising.

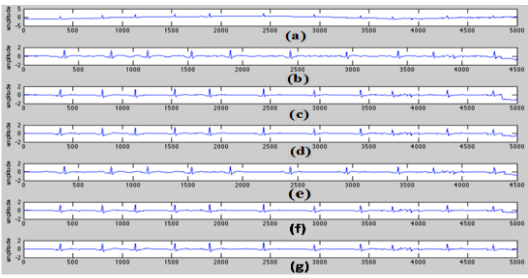

Fig.4 (a) Noisy signal (b) Denoised signal using EMD and static morphological operators (c) Denoised signal using EEMD and static morphological operators (d) Denoised signal using CEEMD and static morphological operators (e) Denoised signal using EMD and adaptive morphological operators (f) Denoised signal using EEMD and adaptive morphological operators (g) Denoised signal using CEEMD and adaptive morphological operators.

Table.3. Comparision between performances of different cascaded combinations

Parameter	Method					
	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
Output MSE	0.0022	0.0017	0.0015	0.0014	0.0012	0.0010
Output SNR (dB)	26.369	32.314	34.596	36.196	38.257	40.276
Correlation Coefficient	0.8869	0.9261	0.9427	0.9353	0.9406	0.9656

(Input SNR = -16.2870 Db; Input MSE = 0.4096)

Case 1: EMD & Static MF
Case 2: EEMD & Static MF
Case 3: CEEMD & Static MF
Case 4: EMD & Adaptive MF
Case 5: EEMD & Adaptive MF
Case 6: CEEMD & Adaptive MF

It can be clearly seen, adaptability enhances the denoising property of filter in cascaded combination also and cascaded combination of CEEMD and adaptive filter gives the best results.

4. CONCLUSION

Results clearly indicate a superior performance of the proposed denoising algorithm over all latest methods for a wide range of ECG data. The algorithm shows significantly improved results over existing methods while testing on real stress ECG signals. The main points of advantage observed are the efficiency in removal of the Baseline Wander noise coupled with the preservation of the morphology of the ECG signal. Further the ability to adapt towards changes in heart rate is another major advantage. The main contributory factors for this advantage are the nature of both of the filters applied. Future work in this area could include reduction in computation times of CEEMD. Despite the fact that a modified and faster version of EEMD is used in proposed method, there is further scope for reduction in the computation time.

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