

# Elimination of mode mixing and R-peak detection of ECG signal by differentiation and decomposition using CEEMD algorithm

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## **ABSTRACT**

*This paper works on the algorithm based on complete ensemble empirical mode decomposition for the electrocardiogram signal. The CEEMDAN algorithm averages the modes obtained through EMD by applying several realization of Gaussian white noise. During decomposition mode mixing occurs which can be rectified in two ways either by differentiation or by decomposition. In this paper, mode mixing has been eliminated by combining differentiation and decomposition by CEEMDAN algorithm. Hilbert transform is used for conversion of ECG signal into the analytical signal for the detection of R-peaks and mean instantaneous frequency.*

*Keywords- Complete ensemble empirical mode decomposition with adaptive noise(CEEMDAN) Electrocardiogram (ECG), Empirical mode decomposition (EMD), Ensemble empirical mode decomposition(EEMD), Intrinsic mode function(IMF), Instantaneous frequency(IF), Covariance(CoV), Hilbert transform(HT)*

## **I. INTRODUCTION**

Electrocardiography is defined as the process of recording the electrical activity of the heart over a period of time by placing electrode on the skin. The ECG signal consists of low amplitude voltages in the presence of high offsets and noise. These signals are within the frequency range of 0.05Hz to 100 Hz. A lot of work has been done in the field of ECG signal analysis using various approaches

and methods. The basic principle of all the methods however involves transformation of ECG signal using different transformation techniques including Fourier Transform, Hilbert Transform, Wavelet transform etc. Physiological signals like ECG are considered to be quasi-periodic in nature. They are of finite duration and non-stationary. Hence, a technique like Fourier series (based on sinusoids of infinite duration) is inefficient for ECG. On the other hand, wavelet, which is a very recent addition in this field of research, provides a powerful tool for extracting information from such signals. Wavelet Transform is an effective technique for denoising the ECG signals which are corrupted by non-stationary noises, also it has a better capability of peaks detection of ECG signal [1]. Empirical mode decomposition is a technique used for the analyses of non-stationary and non-linear signals such as ECG signals [2]. It is an adaptive technique which was first pioneered by N.E.Huang et al in 1998 that separates the slower and faster oscillation of the signal [3]. During decomposing noisy signals the problem of mode mixing occurs. In Mode mixing disparate amplitude and similar oscillations are present in

different modes of the ECG signals. This will increase the complexity of the decomposed signal [4] as amplitude of each harmonic are far apart that cannot be separated by EMD algorithm. Its solution proposed by the Shuen-De Wu, Jin-Chern Chiou and Egeny Goldman by differentiating the non-stationary multiple harmonic signal makes the amplitudes of each close to each other without increasing the number of iteration[5]. Also to overcome this problem a complete ensemble empirical mode decomposition can be used[6]. In CEEMD, ECG signal are decomposed with white Gaussian noise. Addition of white Gaussian noise in the ECG signal resolve the mode mixing by populating the whole time-frequency space to take advantage of the dyadic filter bank behaviour property of the EMD [7]. CEEMD decompose the IMF components which is the mean of the corresponding IMF obtained through EMD over an ensemble of trials, generated by adding different realization of white noise to the original ECG signal  $x(n)$ [8]. CEEMD algorithms steps are follows

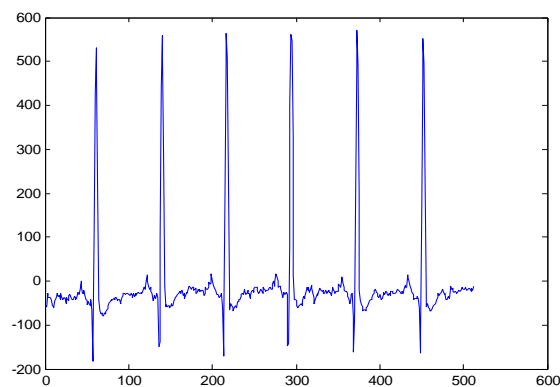
- Generate  $x^i[n]=x[n]+w^i[n]$ , where  $w^i[n]$  ( $i=1, \dots, I$ ) are different realization of Gaussian noise.
- Each  $x^i[n]$  ( $i=1, \dots, I$ ) is fully decomposed by EMD getting their modes  $IMF_k^i$ , where  $k=1, \dots, k$  indicates the modes of ECG signal.
- Assign  $\bar{I}_k$  as the  $k^{\text{th}}$  mode of  $x[n]$  which is obtained by averaging the corresponding  $IMF_k^i$  described in equation(1)

$$\bar{I}_k[n]=1/I \sum_{i=1}^I IMF_k^i \quad (1)$$

Just like EEMD algorithm CEEMDAN algorithm add white noise in the ECG signal with lesser number of iterations. White noise is necessary to force the ensemble to exhaust all possible solutions in the sifting process, thus making the different scale signals to collate in the proper intrinsic mode functions (IMF) dictated by the dyadic filter banks[9]. The added white noise is to provide a uniform reference frame in the time-frequency space [10]. In our paper ECG signal are first differentiate and then decomposed into the intrinsic mode function by CEEMDAN algorithm. Differentiation removes mode mixing and simultaneously reduce the number of iteration for the ECG signal. We are also able to calculate the mean instantaneous frequency and covariance percentage. This paper divides into two section. In section I differentiation and decomposition ECG signal into the intrinsic mode function that eliminates the problem of mode mixing. Section II describes R-peak detection for CEEMD algorithm with differentiation and Hilbert transform.

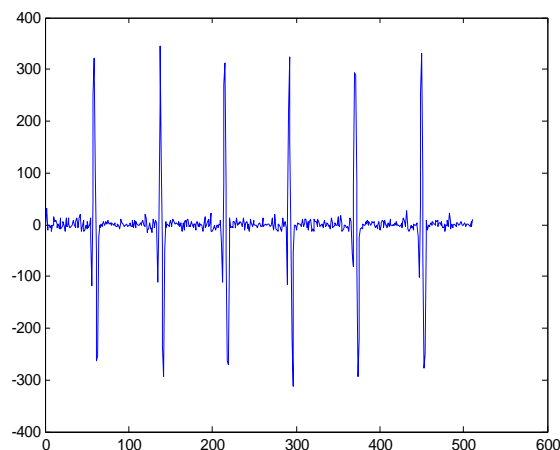
## II. DECOMPOSITION INTO INTRINSIC MODE FUNCTION

A mono-component signal called as intrinsic mode function was proposed by Huang et.al[1] in 1998 or IMF is the type of functions that satisfies two condition.(1)In the whole data-set, the number of extrema and the number of zero crossings must either equal or differ at most by one.(2)At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The original signal is decomposed into a sum of intrinsic mode functions (IMFs) by using shifting process. The first separated IMF components have the highest frequency while the finally separated IMF components have the lowest frequency. The remained component is only a monotonic function with only one extreme point. The upper and lower envelope curves are partially symmetric with the time axis and any two IMF are independent. A typical Ecg signal are represented in Fig(1) for 512 samples



**Fig1.ECG signal for 512 samples**

ECG signal consists of sum of many harmonics with different amplitude levels. By differentiating the ECG signal as shown in Fig(2) the amplitude level of each harmonics close to each other that will eliminates the mode mixing before decomposition.



**Fig2.Differentiated ECG signal**

Now the differentiated signal are decomposed into the intrinsic mode function by CEEMDAN algorithm which removes the low frequency noise component by adding white noise into the differentiated ECG signal. Decomposition without differentiation of ECG signal for 512 samples are shown in fig(3) that contains 11 IMF components. But in decomposition of differentiated signal requires the 10 IMF for the same number of iteration and realization as shown in fig(4). The number of modes for 10 IMF as shown in fig(5).

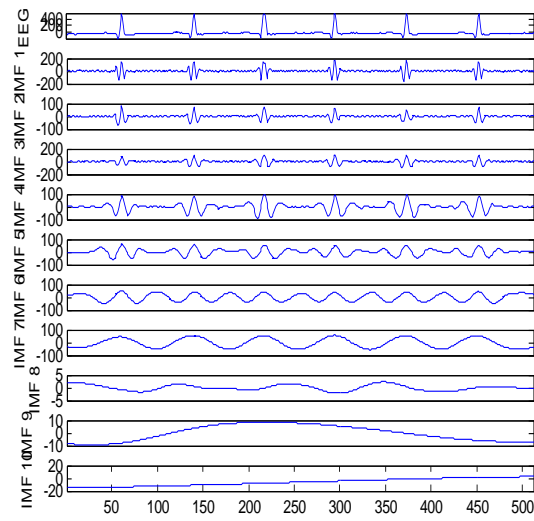


Fig3. Decomposition with mode mixing in ECG

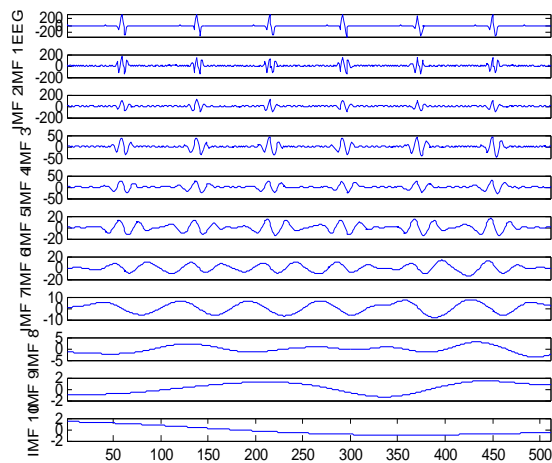


Fig4. Decomposed differentiated ECG signal

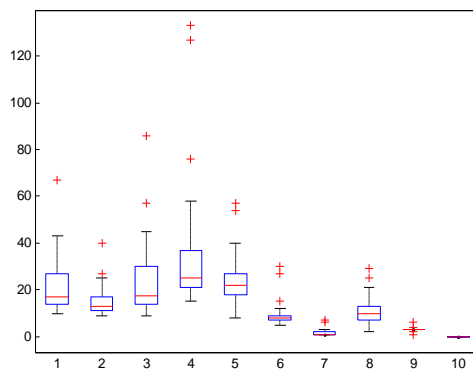


Fig5. Number of modes required for 10 IMF

### III. R-PEAKS DETECTION

ECG signal can be expressed as repetitions of P-QRS-T waves. The basic principle behind the analysis of ECG signal is finding the QRS complex. R peak detection is the 1st and foremost step in finding the QRS complex. Various methods have been implemented in the recent past for R peak detection including Fourier Transform, Hilbert Transform, Difference Operation Method, Wavelet Transform, Empirical Mode Decomposition etc. Hilbert transform for R-peak detection for analytic signal  $c(t)$  is expressed in equation(4) and instantaneous frequency  $w(t)$  as shown in equation(5) as

$$c(t) = f(t) + jh(t) = A(t)e^{j\theta(t)} \quad (4)$$

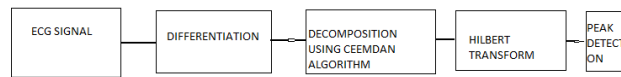
$$w(t) = \dot{\theta}(t) = \text{Im} \left[ \frac{c'(t)}{c(t)} \right] = \frac{f'(t)}{f(t)} \quad (5)$$

The envelope  $b(t)$  of  $y(t)$  can be derived from equation(4) as

$$B(t) = \sqrt{f^2(t) + h^2(t)} \quad (6)$$

The envelope determined using (6) has the same slope and magnitude of the original signal  $x(t)$  at or near its maxima. Moreover  $B(t)$  is always a positive function as can be seen from (6). Hence, when  $x(t)=0$ , the maximum contribution to  $B(t)$  is given by the Hilbert transform. So if we have to find the peaks, i.e. the points where  $\dot{B}(t)=0$ , then indirectly we need to find the maximum contribution to the envelope of the first differential of the ECG. This is the basic principle underlying the use of Hilbert Transform in R-peak detection,

The algorithm for the proposed method can be described from the block diagram as shown in fig(6).



**Fig6. Block diagram of proposed method**

### SIMULATION RESULTS

Simulation result shows step by step process for the detection of R-peaks, which is the important parameter for finding the QRS complex. The QRS complex is used to determine the axis of the electrocardiogram, although it is also possible to determine a separate P wave axis. The duration, amplitude, and morphology of the QRS complex are useful in diagnosing cardiac arrhythmias, conduction abnormalities, ventricular hypertrophy, myocardial infarction, electrolyte derangements, and other disease states.

Hilbert transform for 512 samples of ECG signal with and without differentiation as shown in fig(8) and fig(9) respectively. During decomposition instantaneous frequency of the 2<sup>nd</sup> IMF is helpful to find mean instantaneous frequency of the ECG signal as shown in fig(10) and fig(11) and covariance percentage of various denoising technique of ECG signal.

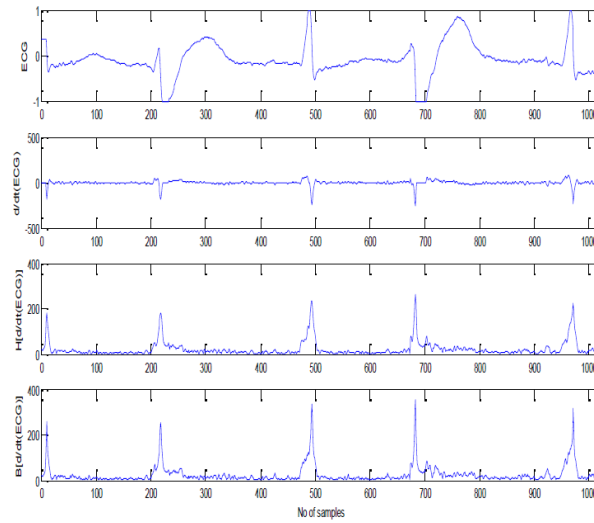


Fig12.Step by step representation for the the Hilbert transform

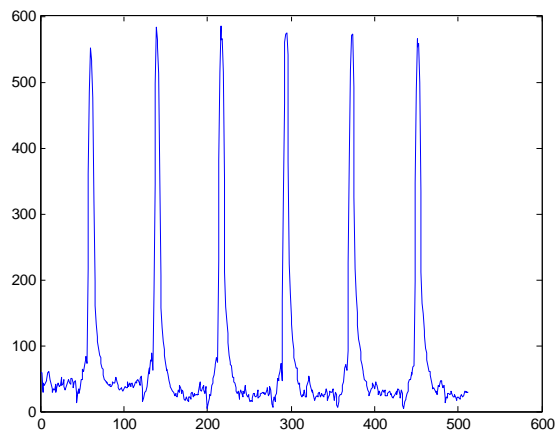


Fig8.Hilbert transform of 512 sample of ECG

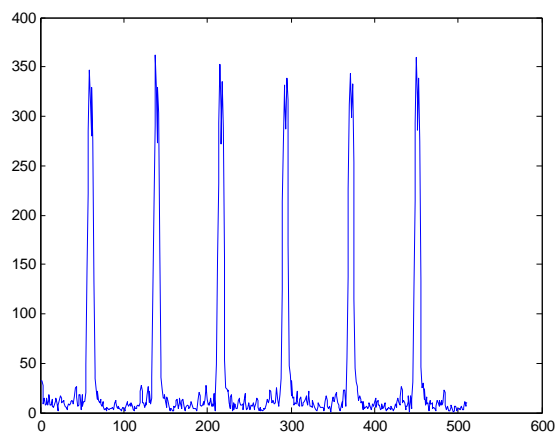


Fig9.Hilbert transform of 512 sample of differentiated ECG

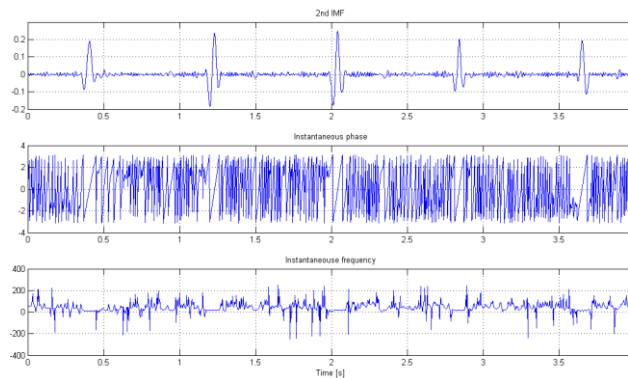


Fig10. Instantaneous frequency and phase of 2<sup>nd</sup> IMF

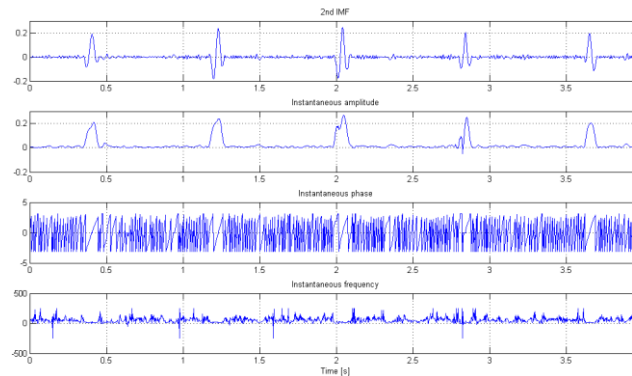


Fig11. Instantaneous Amplitude, frequency and phase of 2<sup>nd</sup> IMF

#### IV. PERFORMANCE AND RESULT

TECHNIQUE	SNR=1		SNR=10	
	Mean IF	CoV(%)	Mean IF	CoV(%)
CWT	0.99	3.34	0.99	1.08
HT	0.9	35.8	1	1.48
CEEMDAN	0.89	2.65	0.3	1.50
CEEMDAN+HT	0.85	3.58	0.87	1.53

Table1. Comparison of other technique with CEEMDAN+HT

In the above table mean IF reduces to 66.2% by increasing the the SNR from 0.7 to 10 by applying CEEMDAN algorithm. But the covariance percentage ideally follows the the denoising property of wavelet transform.

#### V. CONCLUSION

A complete ensemble empirical mode with adaptive noise technique is also data driven technique like EMD but this technique reduces the number of iteration as compared to simple EEMD because due to differentiation

property of the the harmonics of the non-stationary signal that removes the mode mixing problem of ECG. With CEEMDAN and Hilbert transform of decomposed IMF is helpful to find the R-peak of the ECG signal. This mean instantaneous frequency and covariance percentage clearly specified that proposed method with additive noise performed same as other decomposition technique with suppression of more noise.

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