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Various Denoising Techniques Utilization For Qualitative Analysis of ECG Signal: Towards the Proper Diagnosis of Cardiovascular Disease

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Various Denoising Techniques Utilization For Qualitative Analysis of ECG Signal: Towards the Proper Diagnosis of Cardiovascular Disease

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Abstract

Electrocardiogram (ECG) is an extremely powerful method for cardiovascular disease identification. Nevertheless, the ECG data is corrupted during the recording of ECG signals by several forms of noises as for example, power lines interference, base lines wandering, electrode movement, muscle movement (EMG) etc. Such noises / artifacts confuse the proper diagnosis of heart ailments and therefore their removal is much needed. Up to some degree traditional filters exclude the artifacts, but these filters are static and cannot adjust their coefficients to environmental change. Adaptive filtering algorithm and EMD are also utilized to exclude artifacts from the ECG signals. To decompose a signal whose IMFs represents the mean of a set of measurements, each consisting of a signal plus a white finite amplitudinal noise.

Keywords: Electrocardiogram (ECG), Empirical Decomposition Mode (EMD), Cardiovascular Disease, Qualitative Analysis

1. Introduction

ECG is essentially a graphical representation of heart beat- signals and their features utilized to diagnose heart defects. The ECG signal experiences many forms of objects during the acquisition of the ECG.[1]. Such artifacts significantly affect the ST section, decrease the resolution of the signal frequency, present broad amplitude signals in ECG that may mimic PQRST wave forms and hinder proper clinical diagnosis and monitoring. One essential task for better diagnosis is to resolve these artifacts in ECG signals. A major problem to address ECG signals is recovery of high-resolution images from polluted background noise. The objective of improving the ECG signal is to discern the correct signal from unnecessary components of the objects, to provide ECG, which facilitates easy and accurate interpretation of the ECG, which facilitates easy and accurate interpretation.

Human heart consisting of 4- chambers, Right Atrium (RA) Left Atrium (LA) are the upper chambers, Right Ventricle (RV) and Left Ventricle (LV) are the lower chambers. There is a fibrous tissue through which the atria are fixed. This tissue is not connected to the ventricles, which causes the ventricles to be electrically isolated. Both RA and RV from a pump which

pumps blood into the lungs together. RA flows RV oxygen deficient blood provided by large veins (the upper and lower cavemen). RA contracts and causes the blood to enter RV, stretch the ventricle and improve the strength of its pumping (contraction). The blood is then injected into the lungs by RV where it is oxygenated [2]. Likewise, LA and LV together form a pump for the movement of oxygenated blood collected via the pulmonary veins between the lungs and the rest of the body. A sino atrial node (SA) within the heart, a complex electrical conducting system located below the RA in the heart, sends electrical signals to expand and contract the heart chambers and this SA node is known as a pacemaker Since electrical pulses can be activated at a higher rate of 100 p/m. Four waves called as P, Q, R, S and T are registered during heart beats when measuring the ECG signal, as shown in Fig. 1. The generation of the signals and their distribution are explained below. To make the contract of the atria, P wave displays the signal spread from SA node. P-Q Segment represents how signal arrives in an instant via stay of the AV node to allow blood to fill the ventricle. The Q wave demonstrates how the ECG signal is split into two limbs (branches) following his Buddle, and passes through the septum. RA contracts, allowing the blood to penetrate the RV, stretch the ventricle and increase its pumping power (contraction)[3] [4].
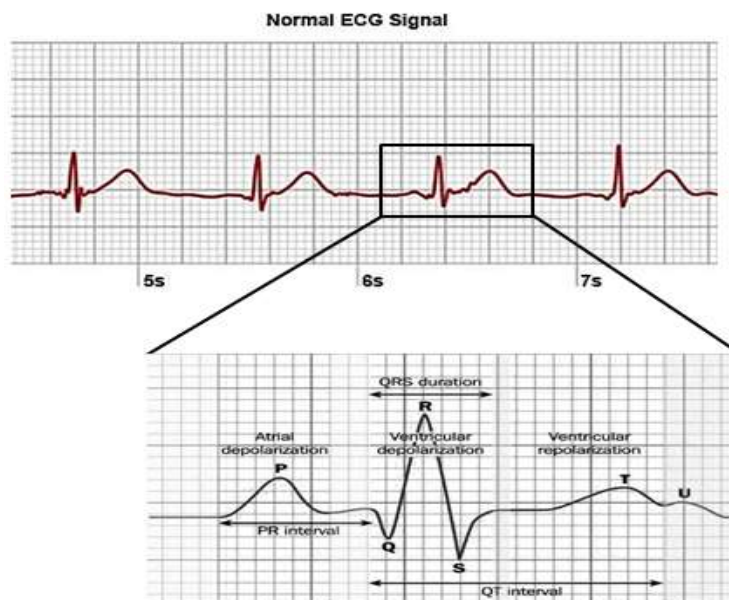
Figure 1, Normal ECG Signal with Details of ECG-Segment

To overcome artifacts encountered during ECG recording, many approaches have been proposed and utilized. However, each of them has certain limitations, hence biomedical research continues to achieve accuracy in signal quality by effectively denoising the noises. In the present work, adaptive algorithms like LMS and NLMS were utilized in addition to EMD and EEMD to denoise the ECG signals and their comparative performance is described.

Figure 2, Normal ECG Signal with Record # 121 MIT-BIH Dataset

1.1 EMD

EMD has confirmed to be a very robust method for signal data extraction from both nonlinear and non-stationary noisy systems. This technique was suggested by Huang et al. [5] [6]. EMD's main downside is the recurrent occurrence of mixing mode, frequently described as a single intrinsic mode feature involving a globally desperate scale signals of a that reside in different components of the IMF. Mathematically, EMD separates the multi-component x(t) signal into "L" number of IMFs, that is defined as:

$$x(t) = \sum_{z=1}^{L} e^{(z)}(t) + d(t) \quad (1)$$

Where d(t) is the remaining nonzero implies that the function differs steadily with only a few extremes[7]. To estimate each residual multi-signal an iterative process called sifting is utilized:

$$x^{(z)} = \begin{Bmatrix} x(t) & z = 1 \\ x(t) - \sum_{j=1}^{i-1} h^{(z)}(t) z \geq 2 \end{Bmatrix} \quad (2)$$

1.2 EEMD

A new method of data analysis aided by noise called EEMD is proposed to address the size separation problem found with EMD without adding a conditional intermittent check. This approach identifies the actual composed of the IMF as the mean of a test set involving a signal plus a white finite amplitude noise. Utilizing this approach, it is evident that a prior subjective criterion will distinguish the scale naturally [8]. To generalize this concept of a group, the noise is combined into one set of data x (t) as if separate observations were actually made as a counterpart to a repeating physical experiment. The white noise applied is known to be the potential normal noise to be encountered during the process of the measurement.

$$x_z(t) = x(t) + K_z(t) \quad (3)$$

When it comes to observation, some of the multi-observation ensembles is imitated by applying multiple random and distinct copies of Wi(t) white noises to the particular observation. When including noise which results in a lower to-noise signal ratio, the added white noises produces a simple distribution of the reference scale to allow for EMD. The low signal-noise ratio therefore does not hinder the phase of decomposition, but merely raises it in order to prevent mixing mode [9] [10]. In analytical mode the decomposition ensemble evolves as follows:

1. To the intended data, add a series of white noises;
2. Break down data into IMFs utilizing integrated white noise;
3. Step 1 and 2 are repeated over and over again, but each time with various white noises series.
4. Obtain the end product of the de-composition-based IMFs for the ensemble means.

The EEMD decomposition results indicate that the white noises series introduced nullifies one another, and the mean IMFs remains inside the normal dyadic filter frames, the probability of combining and maintaining the dyadic property [11] in style is significantly minimised.

1.3 Adaptive Filter (AF)

AF are techniques allow identification of potentials varying in time and analysis of dynamic signal variations. This adapts to adjust the characteristics of the signal so as to minimize error. It is utilized for the cancelation of the adaptive noise, frequency control, device detection and channel equalization. Illustration. 2, Depicts general AF structure.
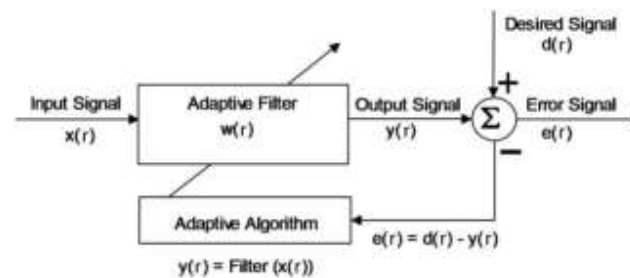

Figure 2, Structure of AF [12]

In AFs, an adaptive algorithm updates the weight vectors to minimize the cost function. LMS and NLMS are important adaptive strategies which are being utilized here.

2. Algorithms Based Techniques

The techniques based on two algorithms can show below:

2.1 LMS Algorithm

LMS algorithm is Bernard Widrow's first widely utilized adaptive algorithm, developed in the 1960s [13]. It finds its place in adaptive digital signal processing and adaptive antenna arrays due in large part to its ease of implementation simplicity and good convergence properties. LMS Algorithms serve as the benchmark for evaluating all other AF algorithms. LMS follows the decent form of stochastic gradients. In that at the present time the filter is only adaptive based on error.

LMS algorithm
Initialisation **K(0)=0** **Algorithm** **for r=0,1,2,---** **y(r)=KT(r)x(r)** **e(r)=d(r)-y(r)** **K(r+1)=K(r)+μx(r)e(r)**

1. Stability of LMS Algorithm

The LMS algorithm can be considered to be a square approximation if the convergence rate parameters are satisfied.

$$0 < \mu < 2/\lambda_{max} \quad (4)$$

The correlation is largest given values of the input signal matrix. But in the practical case, the not Incomprehensible values of the correlation matrix are Eigenvalues, which does not make one (4) very valuable[14]. The beneficial formula in (5) can be derived from and given..

$$0 < \mu < \frac{2}{x(r)^2} \quad (5)$$

The word x(n) is called input signal vector Euclidean norm. It reflects the signal power and is widely known or can be calculated a priority.

3.   Variants of LMS Algorithm

The standard LMS algorithm has a large number of variants and each of them has certain advantages and disadvantages. For instance, echo cancellation requires adaptive algorithm with large memory application and fast convergence but less computational complexity. In another instance like fetal ECG, AF that may require a number of computations with minimum misadjustment is needed [15]. Among various variants of LMS, NLMS has proved its superiority as the most popular one.

3.1 NLMS Algorithm

One of the key drawbacks in traditional LMS algorithms is to have a fixed step-size parameter for each iteration [16]. It then cannot properly monitor the variance of the input signal a better algoritm is the NLMS algorithm, where adaptive to the convergence rate parameter. Here the optimal value of μ for each iteration is determined. And for each iteration the cost function J(w(n+1)) is reduced. Nonetheless, for the entire filter weight vector μ here is the same again. Here, μ indicates to scalar quantity inside that algorithm. This algorithm lightens the gradient amplification barrier in the regular LMS algorithm and avoids unstable filters This algorithm lightens the gradient amplification barrier in the regular LMS algorithm and avoids unstable filters. But that requires a higher complexity of computation. NLMS algorithm computational complexity is 0(N) and includes multiplications of 3N+3.

NLMS algorithm
Initialisation
K(0)=0
Algorithm
For r=0,1,2,---
y(r)=KT(r) * x(r)
e(r)=d(r)-y(r)

It is possible to implement a number of other algorithms and compare their performance with the LMS & NLMS algorithm.

$$\omega(r + 1) = \omega(r) + \frac{\alpha}{x(r)^2 + \beta} e(r)x(r) \quad (6)$$

AF techniques permit time potentials to be detected and complex signal variables to be controlled. For example, an adaptive recurrent filter based on LMS is utilized to obtain the impulse Response of standard ECG QRS complexes and then to detect arrhythmia in ambulatory ECG recordings [18]. The LMS algorithm reference inputs are iImperative functions and are denoted by a regularly extended, truncated set of orthonormal base functions [19]. For these situations, the LMS algorithm works instantaneously such that the weight vector within the event is adjusted for each new sample based on the immediate

gradient's discretion. Many modifications to enhance performance of the LMS algorithm are also recorded in the literature [20]. [21] suggested a noise tolerant phase size variable LMS explicitly designed for biomedical applications. Certain adaptive signal processing techniques such as NLMS are listed aside from those. NLMS algorithm of variable step-size with a faster convergence rate is utilized in this system of the NLMS algorithm, while reducing the size of the step converging to the global minimum. Also, several modifications to boost the of the LMS algorithm efficiency are presented in literature [17,18,19, 20]. In the time domain, [22] presented many adaptive algorithms with less computational complexity. But those algorithms show a slower rate of convergence. A small adjustment to the NLMS algorithm may consequence in a variable stage inversely-proportional to the square base vector error. The error vector length is the number of iterations that instantly occur.

4.   Experimental Outcomes

In order to exam the current proposed method effectiveness, this method has been compared with other algorithms such as EMD, EEMD and AF algorithms such as LMS, NLMS. The MIT-BIH database was utilized to implement all tests performed on ECG signals. Within the Figs. (3-5) The x-axis defined below indicates the number of samples, and the amplitude of the y-axis. Illustration. 3, displays the original MIT-BIH Database ECG signal and Gaussian noise applied to the noisy signal ECG signal. Illustration. 4, describes essential mode features from upper to lowest, where subplots in the vertical axis are not of the same scale. Fig. 5, Analysis of the approaches EMD, EEMD, LMS and NLMS. EEMD approach has better efficiency at 30 dB input SNR in these four systems. Illustration. 6, Depicts the output comparison of different methods utilizing Bar Map.
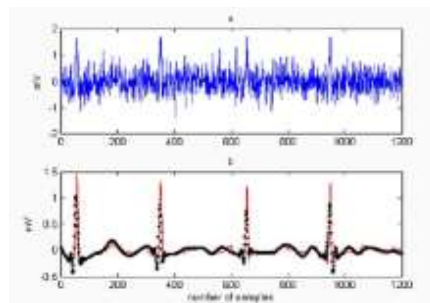

Figure 3. Original ECG Signal(200.dat) MIT-BI Dataset & Noisy ECG Signal With Gaussian Noise
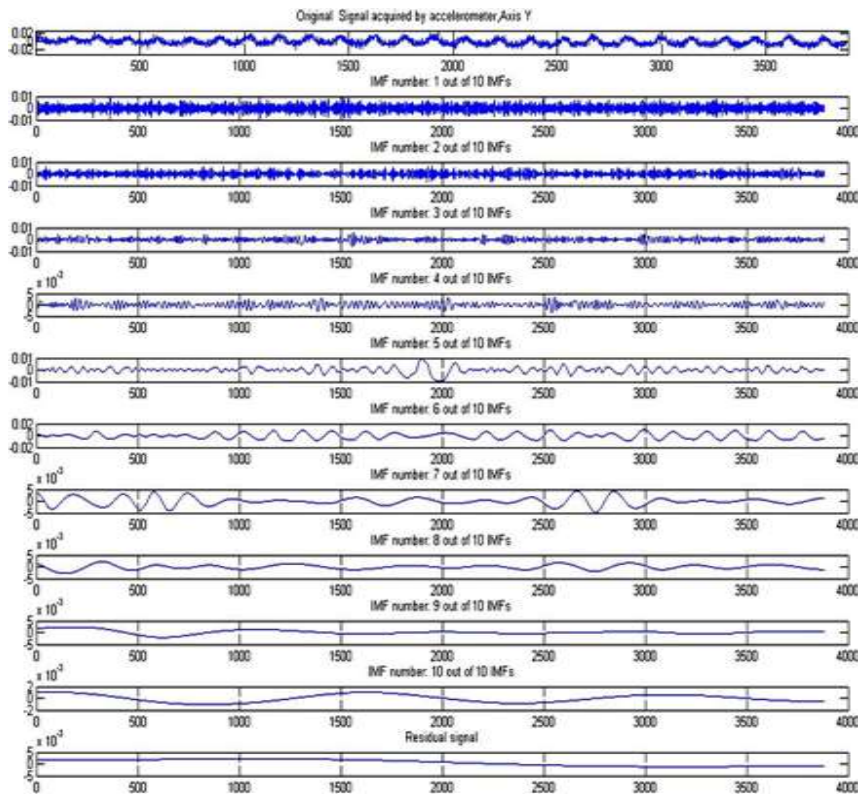
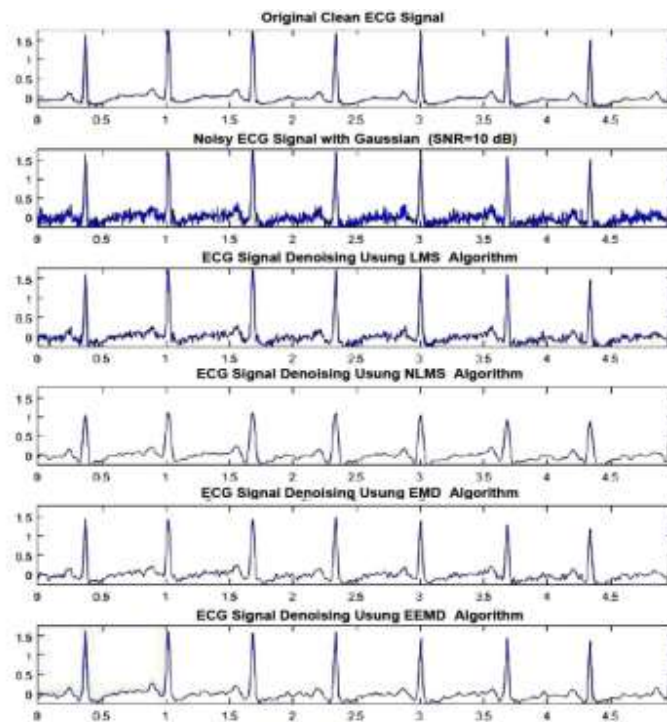Figure 4. IMF s after EMD Decomposition

Figure 5. Record #103 ECG signal After applying various techniques

In table I, 103.data ECG signal from MIT-BIH Data Base at various Input SNRs like 5dB,10dB,15dB,20dB and apply various methods (EMD,EEMD,LMS,NLMS) and get Output SNR values finally EEMD method gives better performance than other methods.

Table -1 SNR values obtained for ECG signal(103.dat) at various input SNRs

The Input SNR	EMD	EEMD	LMS	NLMS
5 DB	52.62	54.11	24.36	27.87
10 DB	52.67	54.15	24.37	27.92
15 DB	52.64	54.13	24.37	27.92
20 DB	52.67	54.17	24.37	27.93
Average	52.65	54.15	24.37	27.92

Table II, shows various ECG signals that were taken from MIT-BIH Data Base and gives fixed Input SNR that is 30 dB and apply various methods finally EEMD method gives better outcomes than other methods. EEMD approach has greatly increased the accuracy of the signals compared to other approaches.

Table -2 SNR values obtained for various ECG Signals at Input SNR is 30dB

| Signal No.	MIT-BIH Database Based ECG Signals Record	Adaptive Methods		Decomposition Methods	
		LMS	NLMS	EMD	EEMD
1	100	23.72	28.73	44.49	50.59
2	101	24.46	27.93	52.74	54.63
3	102	22.56	25.93	55.71	57.80
4	103	24.41	26.73	46.54	46.80
5	104	20.94	26.51	66.73	68.51
6	105	22.73	25.89	51.87	53.88
7	106	23.93	27.96	36.95	38.78
8	107	21.73	23.77	27.70	27.89
9	108	23.63	26.51	43.73	43.87
10	109	22.84	23.98	18.61	18.78
11	110	23.79	26.84	31.67	37.65
12	111	22.62	26.77	72.58	75.47
13	112	23.57	27.61	40.92	41.88
14	113	23.74	27.91	43.91	47.62
15	114	22.21	26.82	61.73	63.75
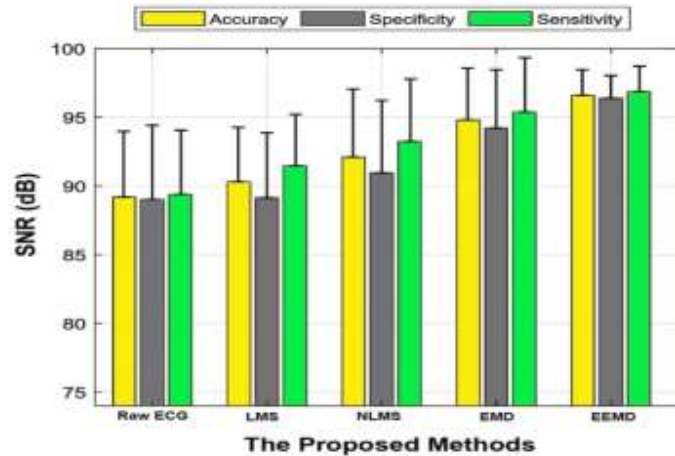
Figure 6. Performance analysis of various approaches

5.   Conclusion

A novel EEMD thresholding method has been suggested in the present study to denoise the ECG signal. This method has been contrasted with the denoising approach of EMD and Adaptive Algorithms such as LMS, NLMS. Experimental findings for an ECG signal selected were tested at various input SNRs at various ECG signals and various output SNRs during the study, it was found that EEMD method significantly enhanced the quality of the signal compared to the other methods. Through the study, it is found that EEMD method leads with other methods of change by around 20 dB-30dB.

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