

Review on Various Methods for ECG Signal Denoising

Madhvi Dasondhi
M.Tech. Scholar, EC Department
Sanghvi Institute of Management &Science, Indore
(India)

Virendra K Verma
H. O. D., EC Department
Sanghvi Institute of Management &Science, Indore
(India)

Abstract –The electrocardiogram (ECG) is used for diagnosis of heart diseases. Good quality ECG is utilized by physicians for interpretation and identification of heart diseases and heart activity. In a few circumstances the recorded ECG signals are tainted by artifacts. Essentially two artifacts are available in ECG signals, high-frequency noise brought about by electromyogram actuated noise, electrical cable obstructions, or mechanical strengths following up on the anodes; baseline wander this may be because of breathing procedure or the movement of the instruments or the patients. So the noisy signal may be the cause of incorrect diagnosis. This paper presents Empirical Mode Decomposition method for denoising of ECG, also introducing other methods for denoising the various methods included are ECG analysis based on wavelet transform and modulus maxima, time-frequency dependent threshold, artificial neural networks and mathematical algorithm using window analysis.

Keywords – Artificial Neural Networks, ECG, Window analysis, ECG denoising.

I. INTRODUCTION

The electrocardiogram (ECG) is the graphical representation of the cardiovascular action and it is utilized to analyze the diseases occurred in heart. The electrocardiogram (ECG) signals demonstrate the impressions of heart's conditions and henceforth any variations from the norm can be discover by breaking down the ECG signals. ECG signals are the nonstationary signals, so it can be exceptionally impossible even for an experienced doctor to do a proper diagnosis. With the presence of computer technologies its applications are helping the researchers all-over the world as they can help with exact examination of the ECG signal [2], [3]. Noises are the main reason of wrong interpretation of the ECG signals that's why preprocessing has to be done to improve the signal quality of ECG signal for further processing. There are two important artifacts that get intermixed with the ECG are high frequency noise that includes electromyogram noise (because of muscle's activity), motion artifacts (because of electrode motion) [4], channel noise (White Gaussian Noise introduced during

Transmission through channels), and power line interferences and the low frequency noise i.e., baseline wandering because of breathing or

coughing [1]. Number of techniques have been reported in the literature for ECG denoising that uses morphological filter to remove the MA Noise [4], adaptive algorithm (RLS) [5], wiener filtering [6], wavelet transform (WT) [7]-[11], advanced averaging technique [12], [13], independent component analysis [14] and BWT (bionic wavelet transform) showing better result over WT [15]. Some of these techniques are based on the prior assumptions of the signal or type of noise available. But practically, it is impossible to obtain information of the signal or noise before processing. Hence, here EMD technique has been used for the denoising of ECG as it is an adaptive mechanism to decompose any signal that doesn't need the prior information and this mechanism is introduced by Huang et al. [16]. Many works have been reported in the literature showing contribution of EMD in biomedical signal processing [17]-[19]. EMD has also been used as a very powerful technique to denoise the ECG Signals [20]-[23].

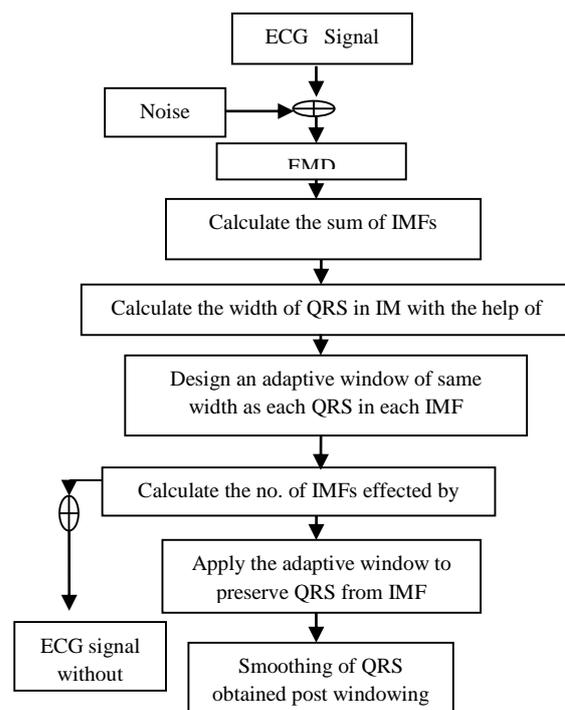


Figure 1: Block diagram of modified EMD based algorithm for denoising of the ECG signal

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II. EMPIRICAL MODE DECOMPOSITION

Empirical Mode Decomposition (EMD) was developed by Huang et al. [16] as a flourishing method for analyzing nonlinear and non-stationary data by decomposing them into a finite and often small number of “intrinsic mode functions” that must follow two conditions: (i) the no of local extrema and the zero crossing must be equal or differ by at most one, (ii) at any point of the time, the mean value of the upper envelope (local maxima) and the lower envelope (local minima) must be zero. The decomposition method simply uses the envelopes defined by the local maxima and minima separately. After finding the extrema, an upper envelope is formed by connecting all the local maxima by a cubic spline line. Similarly the lower envelope is formed by all the local minima. Now their mean is calculated and the difference between the signal data and this mean is found and stated as the first component.

To preserve the QRS complex, we need a delineation of the QRS complex. Experiments show that sum of 1st 3 IMFs

$(im=imf1+imf2+imf3)$ preserves the morphology of the QRS complex [20]. Fig. 2 and 3 shows the plot of the ECG signal and corresponding sum of 1st 3 IMFs for clean and noisy ECG signal respectively. As reported from these figures, the fiducial point locations in the ECG Signal and sum of 1st three IMFs (im) are same. Also these figures reveal that the width of the QRS lie within the two zero crossing points, with one zero crossing point in the left hand side of the local absolute minima and another one at the right hand side of the local absolute minima. Here word absolute has been included due to the fact that sometimes in the case of noisy ECG signal the local minima may lie just near the R-peak (fiducial point). As noise changes the shape of the actual signal, and will create a huge misinterpretation for the actual width of the QRS complex. It has been examined by performing various experiments for both synthetic as well as real noise cases and for the noisy ECG signal (record 103) having white Gaussian noise with 10dB SNR, it is seen that the width of the QRS complex will be lost if the local minima is considered whereas the choice of taking local absolute minima solves this problem of misinterpretation for the actual width to be preserved. Again as we are dealing with the discrete time signal (ECG signal for computer added work and processing), thus many times it is not possible to have the sample value at exact zero crossing point [1].

III. OUTCOME OF EMPIRICAL MODE DECOMPOSITION METHOD

The technique explicated in this work deliberates that on applying empirical mode decomposition to the noisy ECG signal, IMFs include both, the content of the signal as well as noise components, thus only preservation of the useful content of the signal i.e. the actual ECG signal is being considered as the main aim. The proposed method is melioration towards the existing EMD based denoising approaches. This approach of denoising includes the adaptive window technique followed by the smoothing of the preserved QRS complex within the specified QRS duration so that the reconstructed signal achieved is very much similar to the actual ECG signal. The

qualitative as well as quantitative results obtained for various experiments show that the proposed algorithm is very much efficacious and promising one for the denoising of the ECG signal without changing the actual feature of the signal. Here an additional smoothing approach has been introduced to the QRS complex preserved after applying window function. It removes the additional peaks, due to which the actual feature of the QRS complex was deformed caused due to noises. The combination of the modified EMD approach and smoothing makes the algorithm very much realistic and applicable and can be applied in long term examination of the ECG signal in practical stress test as well as in Holter monitoring that may get affected by the prominent noises.

IV. APPLICATION OF WINDOW ANALYSIS IN MATHEMATICAL ALGORITHM FOR DENOISING

This mathematical algorithm is based on two information, one is dominant scale of QRS complexes and another is their domain. This has been done by using a varying-length window which moves over the signal length. Both the noise and base-line wandering signal are evaluated for manually corrupted ECG signals and are verified for true recorded ECG signals.

V. OUTCOME OF APPLICATION OF WINDOW ANALYSIS IN MATHEMATICAL ALGORITHM FOR DENOISING

A mathematical algorithm for denoising ECG signal is proposed here. The advantages of this algorithm are:

- Low response time for ECG denoising
- Mathematically less complex algorithm
- Safely store QRS complex characteristic points, particularly Q and S waves.

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- There are some limitations in this denoising algorithm, these limitations will appear if:
- The morphology of QRS complex is a protracted by small dominant scale.
- Pre-stage detection of R-waves fails.
- The smoothness and morphology preservation of denoised ECG signals strongly depends upon parameters α and β .

VI. NEURAL NETWORK APPROACH TO REMOVE NOISE IN ECG SIGNAL

This ECG denoising method is based on a feed forward neural network using three hidden layers. This method is particularly useful for highly corrupted signals, this approach uses the available ECG channels to rebuild the corrupted channel. We tested the method, on all the records from Physionet MIT- BIH Arrhythmia Database, adding electrode motion artifact noise. This denoising approach enhanced the performance of available ECG analysis programs on corrupted ECG signals.

VII. NEURAL NETWORK ARCHITECTURE AND TRAINING

Neural network with three hidden layers has been used in this system with 1000 units on each layer. The sequence of time segment is used to train the neural network, each one starting five samples after the beginning of the previous one. Fiducial points is not used to create input data to the neural network. Geoffrey Hinton's method [24, 26, and 27] is applied to learn the neural network weights: following initialization using a stack of Restricted Boltzmann Machines, back propagation algorithm is used to fine tune the weights. Refer Hinton [25] for details of the training procedure for Restricted Boltzmann Machines. To reduce the baseline wander firstly we applied a moving average filter, with the window size equal to the sampling rate. Then after we subtract the result from the signal. Median filter is use to remove baseline wander instead of the moving average filter it is more effective as it is. At last, we scaled the output signal to have unit variance and multiplied the input signals by the same scale factor.

We implemented this method by GNU Octave language for reducing training and reconstruction time, we ran the code on a Graphics Processing Unit. The common way to do this is to add noise to an existing signal and measure the Root Mean Square Error (RMSE) of the processed signal relative to the original signal. There are some disadvantages. Firstly, for large data base of ECG it is difficult to avoid noise in the original signal, and

we cannot rely on the denoising method for not reconstructing the noise in the original signal. Another disadvantage is that RMSE does not always react the difficulties in analyzing a noisy ECG. For instance, a constant baseline shift in the reconstructed signal is not very disturbing, but might correspond to a high RMSE value.

This study paper reports RMSE in the reconstructed signal when artificially adding noise in the ECG. Further we evaluated our algorithm using some easily available program that analyze ECG. Comparison of results of applying these programs with and without denoising the corrupted ECG.

VIII. RESULT OF NEURAL NETWORK ARCHITECTURE AND TRAINING

We have Added noise to already available records, and carried out extensive experiments on all the records from the MIT-BIH Arrhythmia Database. Our test shows much better performance when we applied our denoising method to the ECG. QRS detectors show a slight reduction in sensitivity although there is an improvement in the positive productivity. For low noise, above 12db SNR, in our method, the experiments with records mgh124 and sele0106, without adding noise in the test, confirm the advantages of using our method on a real ECG, a Holter record, for example. The experiment with record sele0106 also shows that the result of reconstructing a noisy channel can be extraordinary good when clean channels are available.

IX. RESULT AND ANALYSIS BASED ON WAVELET TRANSFORM AND MODULUS MAXIMA

We have developed a technique of P, Q, R, S and T Peaks detection using Wavelet Transform (WT) and Modulus maxima. The baseline wander removal suppression is one of the common problem in electrocardiogram (ECG) signal processing. To make easier the detection of the peaks P and T we have removed the baseline wander. QRS detection detected these peaks. The proposed method is based on the application of the discretized continuous wavelet transform (Mycwt) used for the Bionic wavelet transform, to the ECG signal. Finally the Modulus maxima are used in the undecimated wavelet transform (UDWT) domain in order to detect the others peaks (P, T) in order to detect R-peaks in the first stage and in the second stage, the Q and S peaks are detected using the R-peaks localization. In order to detect R-peaks in the first stage and in the second stage, the Q and S peaks are detected using the R-peaks localization. In this detection we using a varying-length window that is

moving along the whole signal. For evaluating the proposed method, we have compared it to others techniques based on wavelets. In this evaluation, we have used many ECG signals taken from MIT-BIH database. The obtained results show that the proposed method end-performs a number of conventional techniques used for our evaluation.

X. CONCLUSION

ECG analysis based on wavelet transform and modulus maxima is fast to implement. Whereas in Empirical mode Mathematical algorithm using window analysis technique is based on theoretical facts, which is different from practical facts. In neural network approach to ECG denoising the quality of ECG signal depends upon channel, which cannot be predicted. Decomposition technique the filters are modifiable with data length and main focus is on extracting original ECG signal without or minimum noise, therefore it is the best among the various denoising techniques.

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