Denoising and Artifacts Removal in ECG Signals

Shubhranshu Srivastava

Roll no. 213EC3231

Department of Electronics and Communication Engineering

National Institute of Technology, Rourkela

Rourkela, Odisha, India

May, 2015

Denoising and Artifacts Removal in ECG Signals

Thesis submitted in partial fulfillment of the requirements for the degree of

Master of Technology

in

Electronics and Instrumentation Engineering

by

Shubhranshu Srivastava

Roll no. 213EC3231

under the guidance of

Prof. Ajit Kumar Sahoo

Department of Electronics and Communication Engineering

National Institute of Technology, Rourkela

Rourkela, Odisha, India

May, 2015

dedicated to my parents...

National Institute of Technology
Rourkela

<u>CERTIFICATE</u>

This is to certify that the work in the thesis entitled **"Denoising and Artifacts Removal in ECG Signals"** submitted by ***Shubhranshu Srivastava*** is a record of an original research work carried out by him under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of Master of Technology in Electronics and Communication Engineering (Electronics and Instrumentation Engineering), National Institute of Technology, Rourkela. Neither this thesis nor any part of it, to the best of my knowledge, has been submitted for any degree or academic award elsewhere.

Prof. Ajit Kumar Sahoo
Assistant Professor
Department of ECE
National Institute of Technology
Rourkela

National Institute of Technology
Rourkela

DECLARATION

I,hereby, declare that

1. The work contained in the thesis is original and has been performed by myself under the guidance of my supervisor.

2. This work has not been submitted to any other Institute for the award of any degree or diploma.

3. The guidelines provided by the Institute are duly followed in writing this thesis.

4. All the quoted and written materials from other sources, have been given due credit to the sources by citation and including the necessary details in the references.

Shubhranshu Srivastava

Acknowledgment

I would like to acknowledge the support of my guide **Prof. Ajit K. Sahoo**,whose guidance and support helped me at every step of the research done as well as thesis writing.He encouraged me all the time and kept me motivated and inspired. He helped me to overcome all hurdles in my work.

I am very grateful to my batchmates **Sobhan Kanti Dhara**, **Satish Bhati**, **Rahul Malik** and **Nishchay** for their support, guidance and suggestions. All my lab mates namely **Ravi Ranjan** ,**Pradeep Yadav** and **Kamal** made this task more interesting by discussing various topics and suggesting new ideas.

I would like to extend my gratitude for the support of all my mates in the specialization of Electronics and Communication Engineering .

I would like to avail this opprtunity to express my highest gratitude for my family members for their inspiration and encouragement.

Shubhranshu Srivastava

Abstract

ECG signal is a non-stationary biological signal and plays a pivotal role in the diagnosis of cardiac-related abnormalities. Reduction of noise in electrocardiography signals is a crucial and important problem because the artifacts corrupting the signal posseses similer frequency characteristics as that of the signal itself. Conventional techniques viz. filtering were proved to be uncapable of eliminating these interferences. Therefore the electrocardiography signals requires a noval and efficient denoising strategy with a view to facilitate satisfactory noise-removal performance.

A new yet adaptive and data-driven method for denoising of ECG signals using EMD and DFA algorithms has been investigated..The proposed algorithm has been tested with ECG signals **(MIT-BIH Database)** with added noise such as baseline wander and muscle contraction noise. Parameter are calculated to determine the effectiveness of the algorithm on a variety of signal types. The obtained results show that the proposed denoising algorithm is easy to implement and suitable to be applied with electrocardiography signals.

Contents

List of Figures

List of Acronyms

Acronym	Description
ECG	Electro CardioGraph(Gram)
AWGN	Additive White Gaussian Noise
BW	Baseline Wander
SNR	Signal to Noise Ratio
EMD	Empirical Mode Decomposition
DFA	Detrended Fluctuation Analysis
ICA	Independent Component Analysis

Chapter 1

INTRODUCTION

Overview

Motivation

Objective

Literature Review

Thesis Organization

Chapter 1

INTRODUCTION

An electrocardiogram,or ECG, is a graphical record delivered by an electrocardiograph which records the electrical action of the heart over a period of time [1]. The signal is acquired by measuring electrical potentials between different locations of the body .

ECG signals have an extensive variety of uses all through the medicinal field in figuring out if the heart is working legitimately or experiencing any irregularities.ECG analysis is the highest level for the assessment of cardiovascular arrthymias. It directs treatment and danger stratification for patients with suspected intense myocardial infraction.

1.1 Overview

An Electrocardiogram (ECG) processing system performs its best when the input data is free from disturbances (muscle artifacts, electrode disposition problems etc.). Thus the estimation of the noise presence in an ECG, on the other hand, gives the possibility to the operator or to the computer analyser to reject (a part or the entire ECG segment) or to further continue the computer analysis, according to the noise magnitude present in the ECG [2].

The ECG signal is unfortunately contaminated by various factors during acquisition or transmission which appears as noise .These noisy effects degrade the performance of visual as well as computerized analysis. Thus the noise removal becomes an evident task to facilitate further processing[2]. The de-noising process is described as to remove the noise while preserving the quality and information content of processed signal. The traditional way of de-noising a signal or an image is to use filters. By using these conventional techniques a specific noise type can be eliminated. Major difficulty arises when the noise and the signal ,being analysed, lies in the same frequency band. Then various non-linear techniques are brought in to address this issue.

1.2 Motivation

Signal processing is a field of constant development and improvement. Many innovative techniques and methods are being developed each and every day. These methods helps the signal processing engineers and scientists in extraction of valuable information from a variety of signals. Signal denoising is a field where no single technique can provide help in analysing all types of signals. Keeping in mind the importance of ECG analysis in the area of medical science , hundreds of techniques are avalibale which can process the signal and provide information in various ways. But still no single technique is fully reliable and robust.

1.3 Objective

The objective of this work is to perform a comparative study among the non-linear methods of signal de-noising and artifact cancellation .Varoius methods are applied on ECG signals with varying signal-to-noise ratio. The efficiency and robustness of the methods are also examined and inferences have been given.

1.4 Literature Review

A lot of work has been carried out in relevance of the scope of this report. A brief introduction of some of them is presented in the following:

- S.L.Joshi, et. al. have compiled a summary of various denoising methods [1].

- Mashud Khan et. al. in [3] propose a wavelet based Signal-Noise residue algorithm.This algorithm assumes that the noise adds to the raw ECG signal in linear fashion. The symmlet8 mother wavelet has been used for multi-scale decomposition of the signal which enables accurate estimation of noise and facilitate its removal with minimal computation.

- Bingo W. et. al. in [4] formulated some fuzzy rules to select suitable multi wavelets , pre and post filters at different noise levels. Though an improved denoising performance is achieved, but choosing a membership function is difficult.

- Manuel B. V. et. al. in [5] proposed a method based on Empirical Mode Decomposition. The input series is decomposed into a sum of intrinsic mode functions which represent simple oscillatory modes. Delineation is used to preserve the QRS complex segment . Noisy IMFs are selected by a moving window and excluded in the final reconstruction.

- P. Mithun et. al. in [6] proposed a denoising technique based on wavelets.Their method is advantageous in the sense that it does not need a priori reference as in the case of adaptive filtering techniques.The discrete Meyer wavelet is the selected as wavelet basis function. A new thresholding funtion is also proposed which combines the features of hard and soft thresholding.

- D.Zhang in [7] proposes an approach for baseline wander removal based on DWT. The shrinkage method uses E-Bayes posterior median to reduce the high-frequency noise. Symlet wavelet with order 8 is used for decomposition level up to 6 .

- Wei Zhang et. al. in [8] propose wavelet based sub-band adaptation filter algorithm to extract a weak ECG signal in a high noisy environment. This hybrid approach improves the extracting precision and provides strong stability.

- Md.Ashfanoor Kabiret.al.in [9] proposed a windowing method in EMD domain. Unlike the conventional approaches this method suggest to separate the QRS complex from the first three IMFs. The noisy signal ,after enhancement in the EMD domain , is transformed into wavelet domain where an adaptive thresholding scheme is applied to wavelet coefficients. Then DWT is used to perform adaptive soft thresholding after reconstruction to reduce the residual noise .

1.5 Thesis Organization

Including this introductory chapter, this thesis is divided into four chapters:

Chapter 2: ECG Signal and Its Characteristics

In this chapter, properties of ECG signal is discussed and details about its various specific features is also provided.

Chapter 3 : Empirical Mode Decomposition

In this chapter, Empirical Mode Decomposition is introduced as a novel tool of signal decomposition. Its properties, working procedure and performance metrics are discussed.

Chapter 4: De-trended Fluctuation Analysis

In this chapter, application of De-trended Fluctuation Analysis technique on biomedical signals is discussed. A variety of signals are analysed using the DFA technique. The signals were corrupted by varying noise levels and then the efficiency of DFA technique in estimating the noise levels is examined. Results and discussions have been given in this section.

Chapter 5: Conclusion

In this concluding chapter, performance analysis and limitations of the methods is discussed and final remarks has been given. The scope of future work is provided in this chapter.

Chapter 2

ECG Signal and Its Characteristics

Introduction

Characteristics of ECG Signal

Noises and Artifacts in ECG

Chapter 2

ECG Signal and Its Characteristics

2.1 Introduction

ECG is a graphical record of the electrical activity of the heart. Inner sides of the cardiac cells are negatively charged relative to the outer sides. These cells lose their negativity through *depolarization*. This depolarising wave propagates from cell to cell and thus is transmitted across the cardiac musculature . The electric current produced by this wave is detected by placing the electrodes over body surface . These cells can also restore to their normal polarity level by undergoing *repolarization* [10] .

2.2 Characteristics of ECG Signal

In the ECG record, heart beats are drawn in the series form comprising a battery of electrical waves. These waves have characteristic peaks and valleys which contains useful information.Two types of inferences are drwan from any ECG . First is the duration of electrical wave that crosses the heart and second is second is the amount of electrical activity passing through the cardiac musculature system.

The typical frequency range of an ECG lies is in the range of 0.05 to 100 Hz. A typical ECG signal has five characteristic peaks and valleys which are labelled as $P, Q, R, S, and\ T$. Sometimes a faint peak U is also visible.

The credibility of ECG analysis system is evaluated by its ability to detect these waves namely P and T and the QRS complex. Atrial activation is menifested in P waves where as QRS complex and T-waves indiacates ventricular activity. A faithful and precise detection of QRS complex is of utmost importance in any automatic ECG analysis setup. A detailed examination viz. heart rate measurement , Arrhthmia detection etc. follows Once the QRS complex is identified saisfactorily.

In the normal heart , the values of a few important parameters are listed as follows [10]:

Interval	Duration(seconds)
P-R	0.12- 0.20
Q-T	0.35-0.44
S-T	0.05-0.15
P-Wave	0.11
QRS	0.09

A normal and healthy heart beats 60 to 100 times in a minute. This is known as *NSR* or normal sinus rhythm. A slower rate is called *Bradycardia* where as a higher rate is called *Tachycardia*. The $Sino-Atrial(SA)node$ which is located near the top of the right atrium , controls the electrical activity of the heart. It is also known as *natural pacemaker*. The wave of action potential ends at the $atrioventricular(AV)node$, a point located near the centre of the heart.

The **iso-potential line** or the **baseline** is the horizontal segment of the ECG waveform which preceeds the P-wave. 'P wave' indicates depolarization of atrial muscles. The QRS complex is produced by a simultaneous activity which comprises repolarization of the atria and depolarization of the ventricles.

Ventricular repolarization is menifested in T-wave. Sporadically appearing U-wave, is generally supposed to be caused by the residual potentials in the ventricular muscles.A typical ECG segment is shown in the figure below.

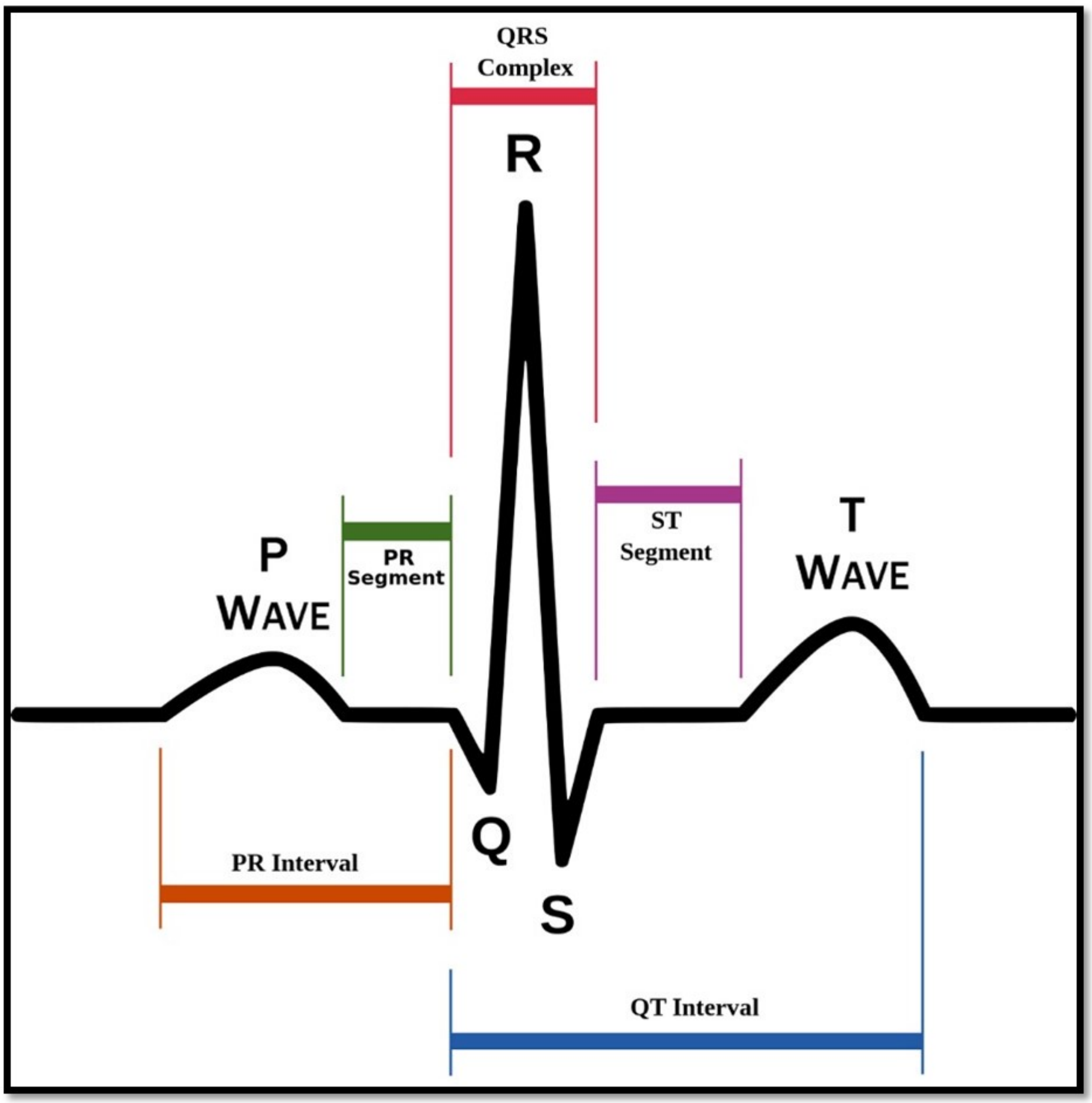


Figure 2.1: A typical ECG trace

2.3 Noises and Artifacts in ECG

The various types of noise which contaminate ECG signals are electrode contact noise, Powerline interference, Baseline wander, Motion artifacts, Musculer contraction and Instrumentation noise [1].

Power line interference: Power line interference means the interference caused by 60/50 Hz power supply to which the machine is connected. Its magnitude can be as high as 50 percent of peak ECG amplitude typically. Some of the common causes for this are [11] :

- Stray effects caused by the alternating current fields .
- Inappropriate grounding of ECG machine or the patient.
- Electrode disconnect.
- Electromagnetic interference due to the power supply.
- Heavy electrical equipment such as elevators and X-ray units draw a large current from the power supply and can induce 50/60 Hz signals(and its harmonics) in the circuitry of the ECG machine.

Electrode contact noise: This is caused by faulty connection between patient and measuring system. Dislocation of electrodes, lack of adhesive jelly etc. are prime factors which causes this artifact.

Motion artifact: Transient changes are induced in the baseline due to varying skin-electrode impedance which is caused by the movement of the patient when the ECG is being recorded [1].

Muscle contractions: It is also known as EMG noise which is induced because of the gross potentials picked up from the body surface by the ECG electrodes. Erratic patient body movement or vibrations is said to be responsible for this[12].The SD of this noise is approximated upto 10 percent of peak ECG amplitude and frequency content ranges from dc(0 Hz) to 10 KHz.

Baseline Wander: It is caused by heavy respirational activity or movement of the thoracic cavity which creates problems in the accurate detection of peaks. Because of this, low amplitude peaks such as T-wavs become high valued and might be mistaken for R peak which is of the highest amplitude in general.

Chapter 3

Empirical Mode Decomposition

Chapter 3

Empirical Mode Decomposition

3.1 Introduction

Empirical Mode Decomposition was proposed by **N.E.Huang** [12] as a novel method for the analysis of nonlinear and time-variant information. It can be utilised to decompose any complex dataset into a small number of Instrinsic Mode Functions(IMFs) which represent fundamental oscillatory modes present in the complex dataset.The decomposition method is efficient as it is fully adaptive and data-derived.This method is appropriate to be applied on a nonlinear process because it is dependent on the local chracteristic time scale of data.

3.2 Intrinsic Mode Functions

As said above , an IMF represents an oscillation mode embedded within the data. Following two conditions must be fulfilled in order to be an IMF :

- The difference between the count of extremas and *zero crossings* should either be zero or equals to one.
- The mean value of the envelopes,as defined by the local maximas and the local minimas, is to be zero.

By virtue of this definition, an IMF consists of only a single oscillatory mode with no complex wave riding on it.

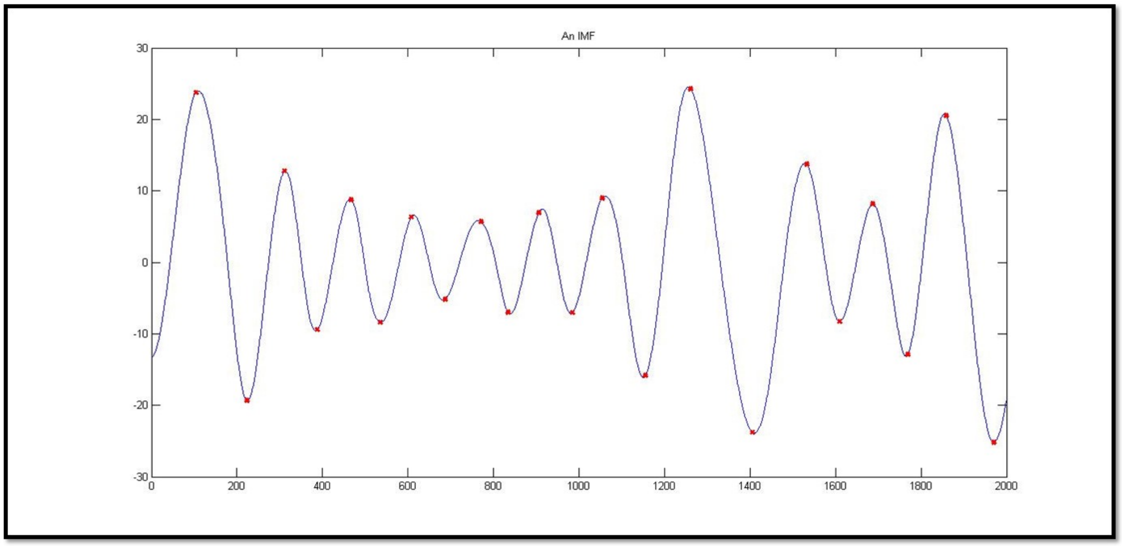


Figure 3.1: An intrinsic mode function

3.3 The Algorithm

3.3.1 Sifting Process

The prime goal of EMD mathod is to identify the fundamental oscillatory modes, by using the characteristic time scales in the data. A systematic way to extract the IMFs is known as *Sifting process* and explained in the following:

1. All the extremas viz. local maximas and local minimas are identified.
2. Local extremas are joined by a cubic spline curve to get the upper and the lower envelopes.
3. Mean value of these two envelopes is calculated as M_1. This mean is subtracted from the data to get the first component H_1, i.e.

$$X(t) - M_1 = H_1 \tag{3.1}$$

4. in the second iteration , H_1 is taken as the data and the procedure is repeated to get the second component H_{11}.

$$H_1 - M_{11} = H_{11} \tag{3.2}$$

5. thus the sifting process is repeated k times , until H_{1k} comes out to be an IMF .

$$H_{1(K-1)} - M_{1k} = H_{1k} \tag{3.3}$$

6. Then it is designated as C_1 , the first IMF component of the data. Then it is separated from the data as ,

$$X(t) - C_1 = R_1 \tag{3.4}$$

where R_1 is a residue which may contains information about the long periodic components. It can be treated as the data in further iterations.
All the subsequent $R_j s$ are then subjected to the sifting process as described and the outcome is shown :

$$R_1 - C_2 = R_2, ..., R_{n-1} - C_n = R_n \tag{3.5}$$

Thus from equations (3.5) and (3.4) , we can get

$$X(t) = \sum_{i=1}^{n} C_i + R_n \tag{3.6}$$

In this way , we get a decomposed form of data into a set of n empirical intrinsic modes and a residue, R_n which is generally a constant or the mean trend.

3.3.2 Stopping Criterion

The sifting process can be terminated after a fixed number of IMFs are obtained.This is done to ensure that the IMF components contains sufficient and enough,in physical sense, amplitude and frequency variations. This is accomplished by defining a stopping criterion as follows:

The Standerd Deviation(SD) is calculated from two consecutive sifting iterations as

$$SD = \sum_{t=0}^{T} \left[\frac{\left| \left(H_{1(k-1)}(t) - H_{1k}(t) \right) \right|^2}{H_{1(k-1)}^2(t)} \right] \tag{3.7}$$

The typical value of SD is choosen between 0.2 and 0.3.

3.3.3 Mode Mixing Problem

The EMD suffers from Mode mixing problem happens during the process. Direct application of $sifting process$ causes the mode mixing due to IMF mode rectification. A specific signal may not be seggregated into the same IMFs every time the process is applied. This problem makes it hard to implement feature extraction, pattern recognition beacause the feature is no longer associated in one labeling index.A possible solution of mode mixing problem is to include an intermittence test during the HHT process [13].

3.4 Ensemble EMD

The EEMD calculates the *true* IMFs as the mean of the corresponding IMFs obtained by using the conventional EMD[14]. These IMFs are obtained from a set of *ensemble* trials. A finite variance white noise is added to the original data series to obtain these trialset.

The EEMD algorithm in illustrated in the following :

1. generate $Y^i[n] = Y[n] + W^i[n]$, where $W^i[n]$ (i=1,...,I) are different realisations of white Gaussian noise.
2. Each $Y^i[n]$ is decomposed by coventional EMD into their modes $IMF_k^i[n]$, where k=1,...,K indicates the modes.
3. Now IMF_k as the k-th mode of $Y[n]$, is obtained as the average of the corresponding IMF_k^i:

$$\overline{IMF_k}[n] = \frac{1}{L}\sum_{i=1}^{L} IMF_i^k[n] \tag{3.8}$$

3.5 Results and Discussions

The EMD is applied on various types of signals and results are shown in the following examples :

3.5.1 Example 1

In example 1, a signal $X(t)$ which is a ombination of signals x_1, x_2 and x_3 , as shown, is decomposed into IMFs. The three distinct components of the signal $X(t)$ is clearly separated in its IMFs.

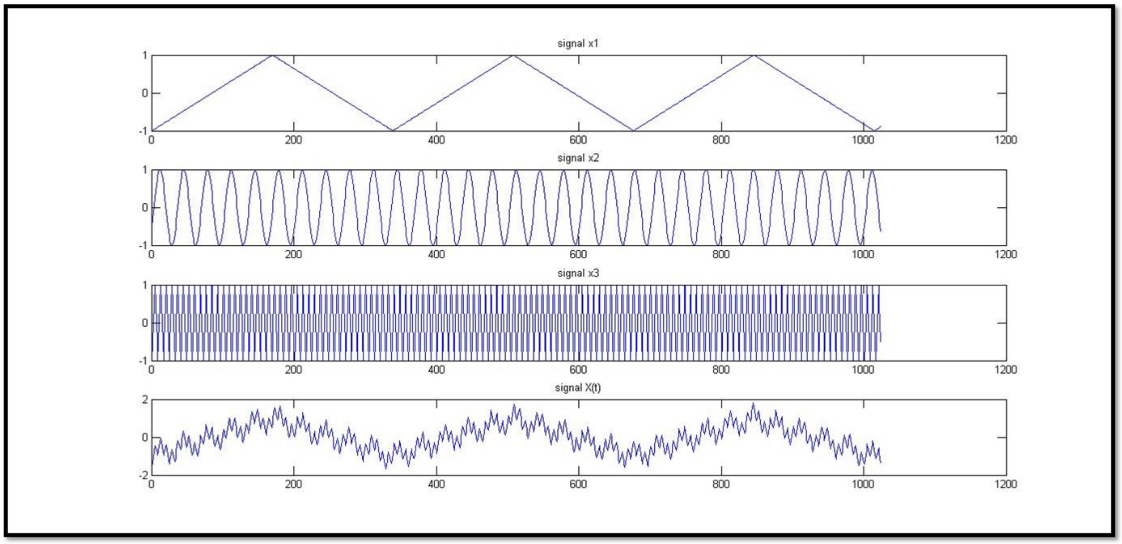


Figure 3.2: mixed signal $x(t)$

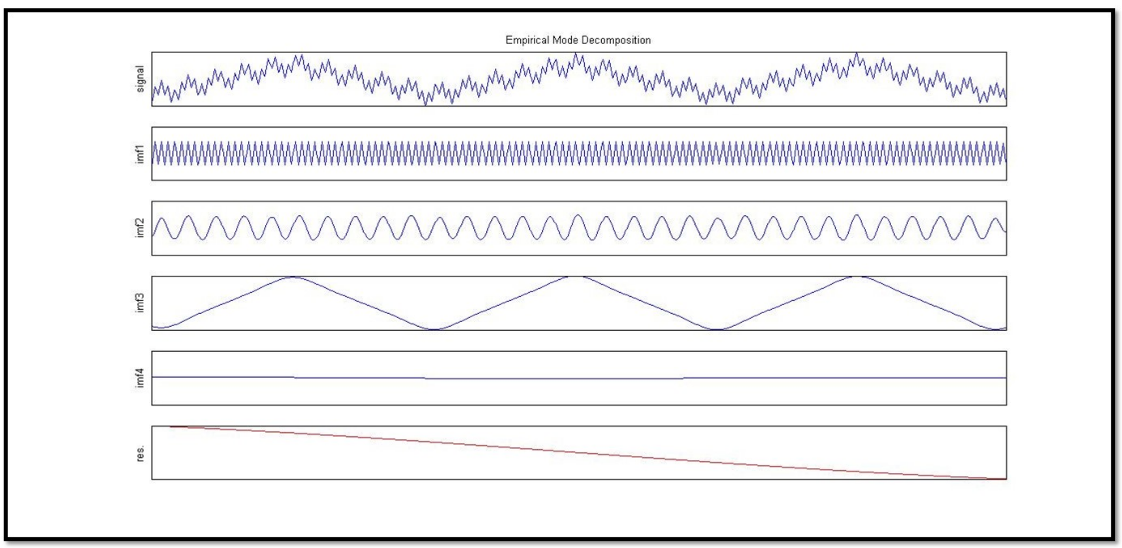
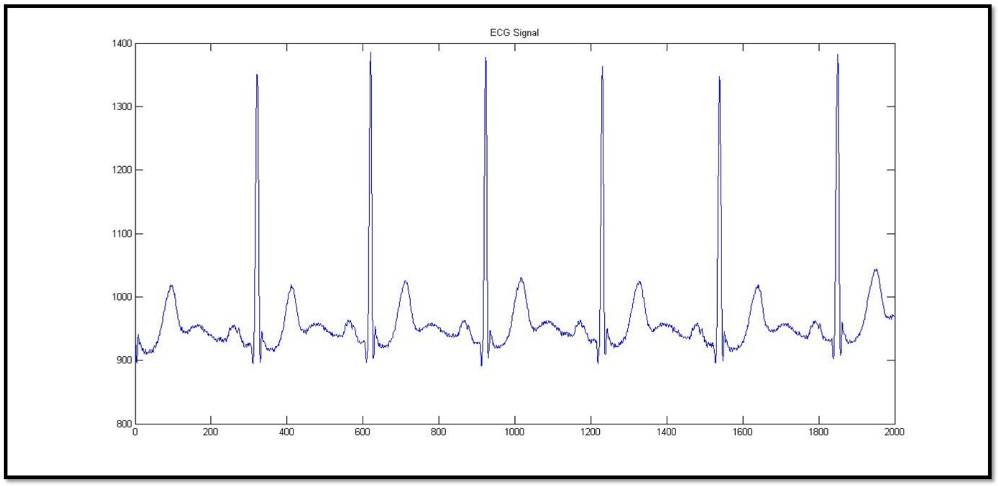


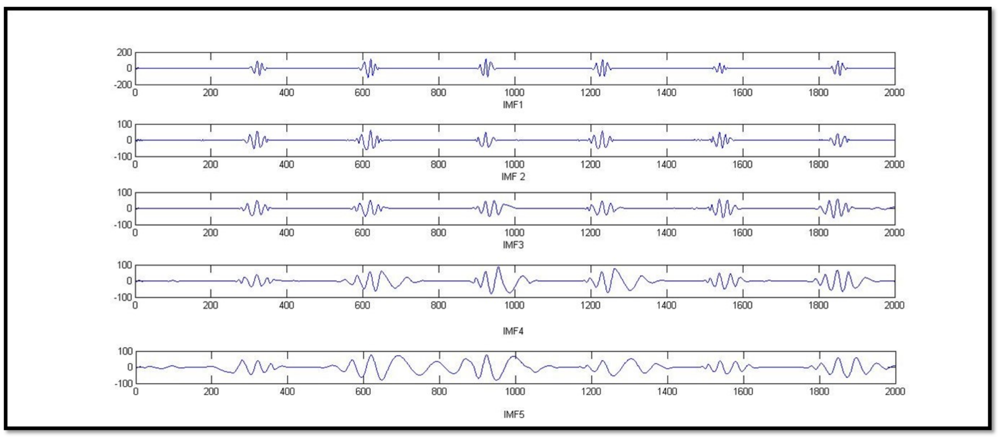
Figure 3.3: EMD of signal $x(t)$

3.5.2 Example 2

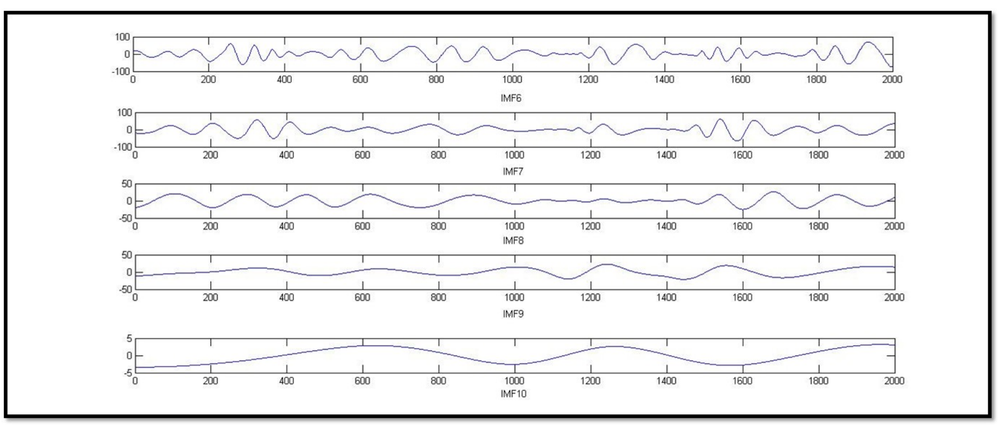
In example 2, a real ECG signal (taken from **Physionet Database**) is decomposed into its IMFs.



(a)



(b)



(c)

Figure 3.4: (a) Clean ECG signal (b) and (c) IMFs of clean ECG segment

3.5.3 Example 3

In example 3, the same ECG signal is contaminated with a fixed amount of noise and then decomposed into its IMFs.

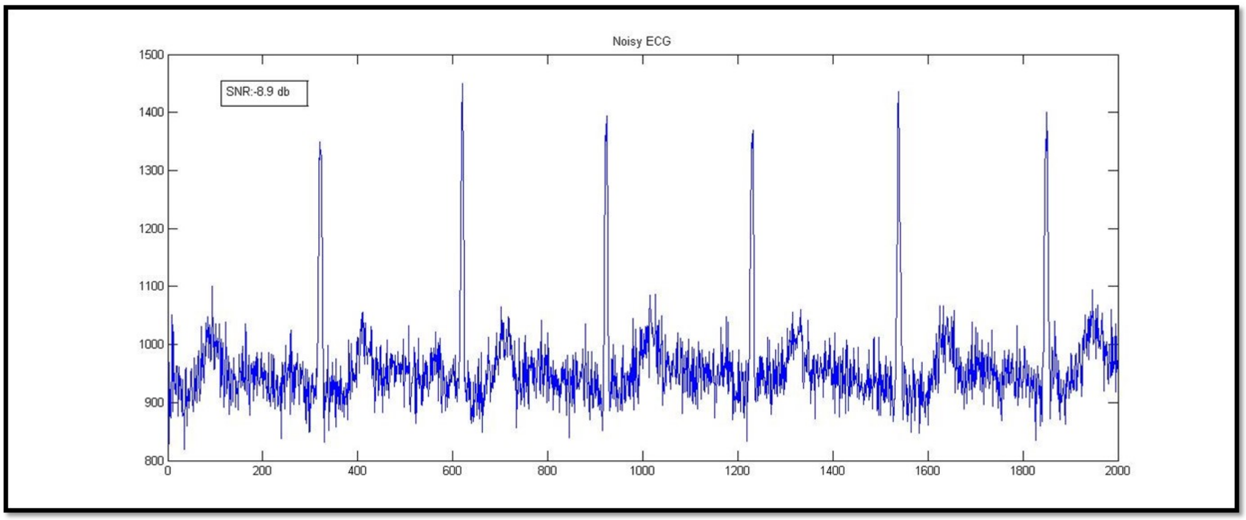
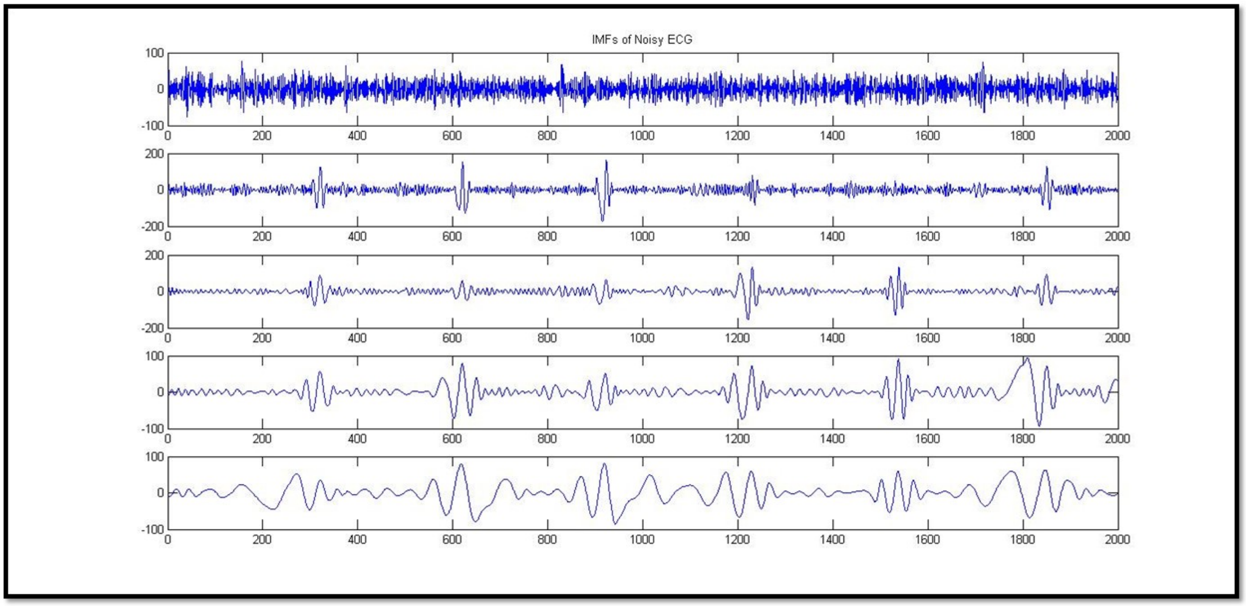
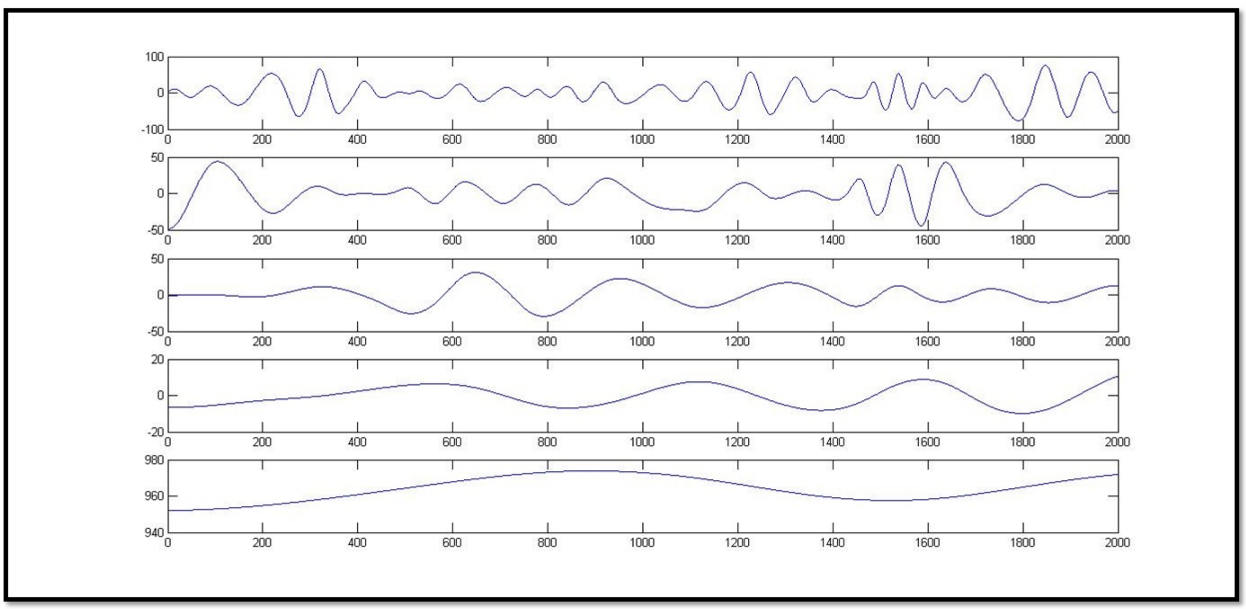


Figure 3.5: Noisy ECG segment



(a)



(b)

Figure 3.6: (a) and (b) Noisy IMFs

Chapter 4

Detrended Fluctuation Analysis

Chapter 4

Detrended Fluctuation Analysis

4.1 Introduction

The Detrended Fluctuation Analysis ,or DFA, is proposed by **C.K.Peng** [15]. It is a newly developed method for obtaining scaling exponent for signals showing non-stationarity.It is useful in analysing signals showing different trends of unknown duration. It facilitates the identification of long-range correlations that are embedded in a non-stationary time series. The DFA score is calculated on a log versus log scale.

4.2 The Algorithm

The fundamental idea of DFA is to assess the variation of the average RMS fluctuation around the local trend as a function of the time scale n. The steps to calculate the DFA exponent of a time series are listed below:

1. An integrated time series is obtained after removing the mean as shown

$$Y(k) = \sum_{i=1}^{k} [y(i) - \bar{y}], 1 \leq k \leq N \tag{4.1}$$

   where $\bar{y}$ is the average value of the time series.

2. $Y(k)$ is then divided into equal sized nonoverlapping boxes of length l.

3. The local trend $Y_n(k)$ is computed in each box by using least square curve fitting.

4. The RMS fluctuation $F(n)$ is calculated by subtracting $Y_n(k)$ from the integrated series $Y(k)$ as:

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left[Y(k) - Y_n(k)\right]^2} \tag{4.2}$$

5. The step 4 is iterated over all time scales (boxsizes) and a relationship between $F(n)$, the average fluctuation, and the box size n is obtained.

6. The fluctuation is quanitatively expressed by a scaling exponent α, obtained from the slope of the line in the plot $log(F(n))$ versus $log(n)$.

4.3 Trend Analysis

The DFA exponent α is the slope of the line relating $log(F(n))$ to $log(n)$. The interpretation of the various values of the α is given below [16] :

1. $\mathbf{0} \leq \alpha \leq \mathbf{0.5}$: No correlation exist between values of different interval i.e. as in the case of *white noise*. This is achieved in a times series where the order of the points has been interchanged.

2. $\mathbf{0.5} < \alpha \leq \mathbf{1}$: This indicates persistently long-range correlations of power law form. If $\alpha = 1$, it refers to $^1/_f$ noise.

3. $\alpha \gg \mathbf{1}$: No power-law form but correlation exists; $\alpha = 1.5$ refers to the case of *Brown noise* , which is obtained by integrating the white noise.

The exponent α is the measure of the "roughness" of the data series. A large value of α indicates a higher degree of "smoothness".

4.4 Results and Discussions

The denoising strategy utlised in this report is the combination of EMD and DFA algorithms. A noisy signal is decomposed into IMFs by using the EMD. Then each IMF is examined by using DFA technique to estimate its noise content. The IMFs with DFA exponent α value less than or equal to 0.5 is omiited. The rest IMFs are used to reconstruct the noise-free approximation of the signal.

4.4.1 Example 1

This example demonstrate the use of EMD algorithm for baseline wander correction in an ECG segment.

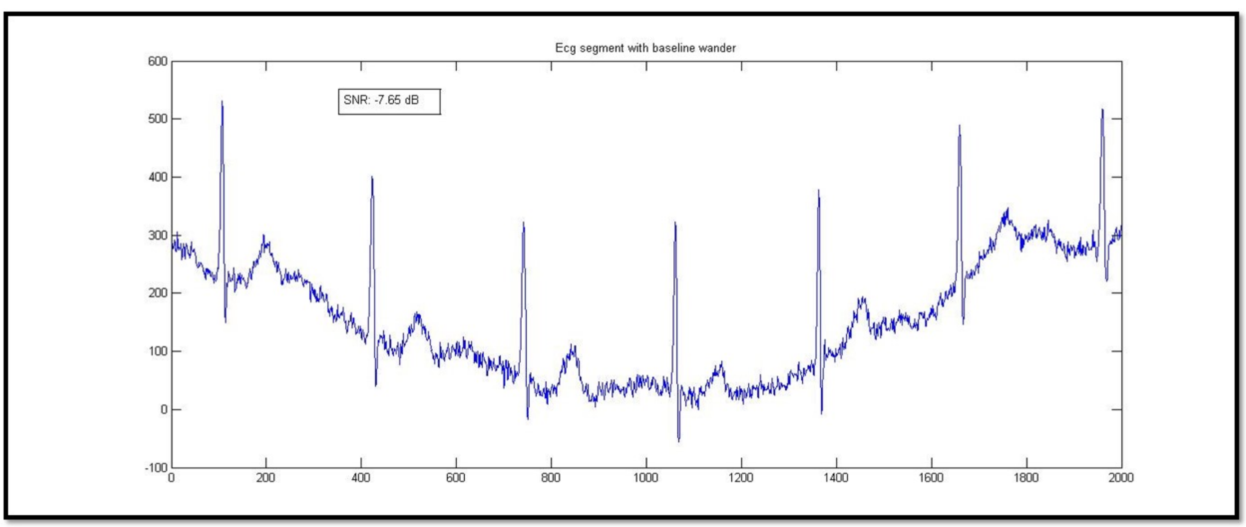


Figure 4.1: ECG segment with baseline wander

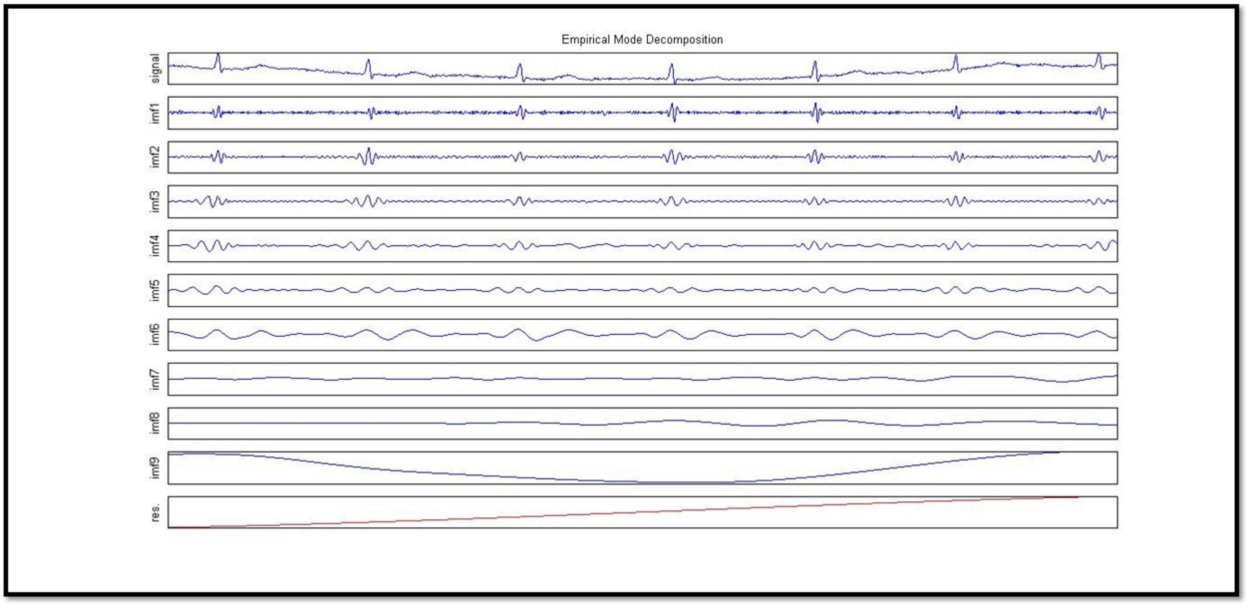


Figure 4.2: BW captured in an IMF

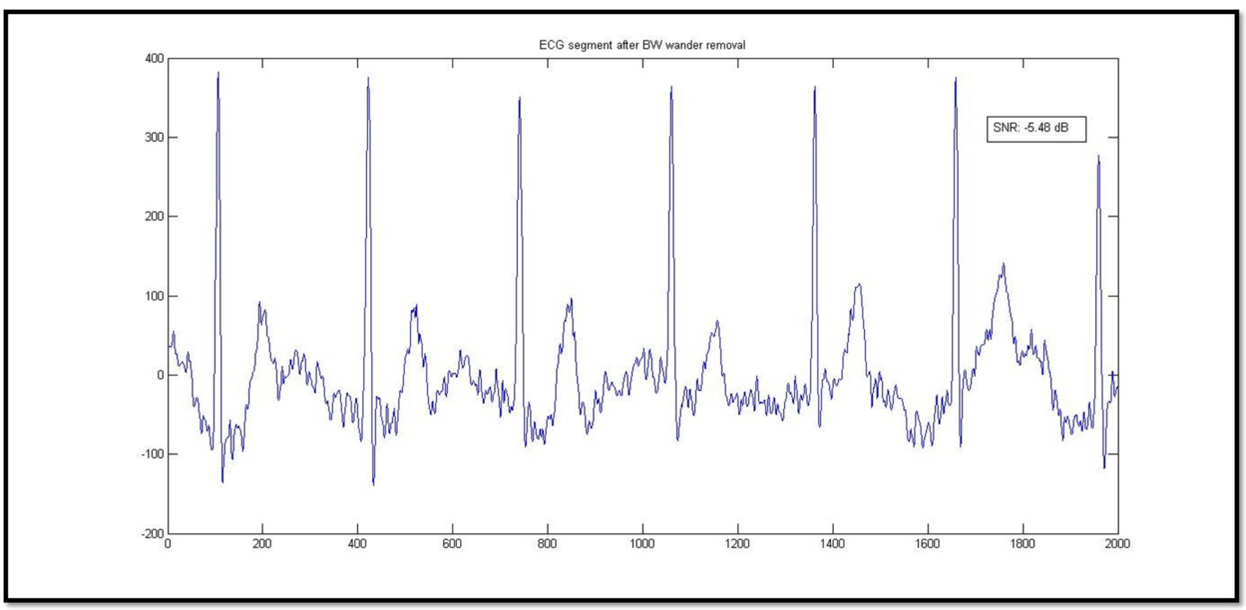


Figure 4.3: ECG segment after BW removal

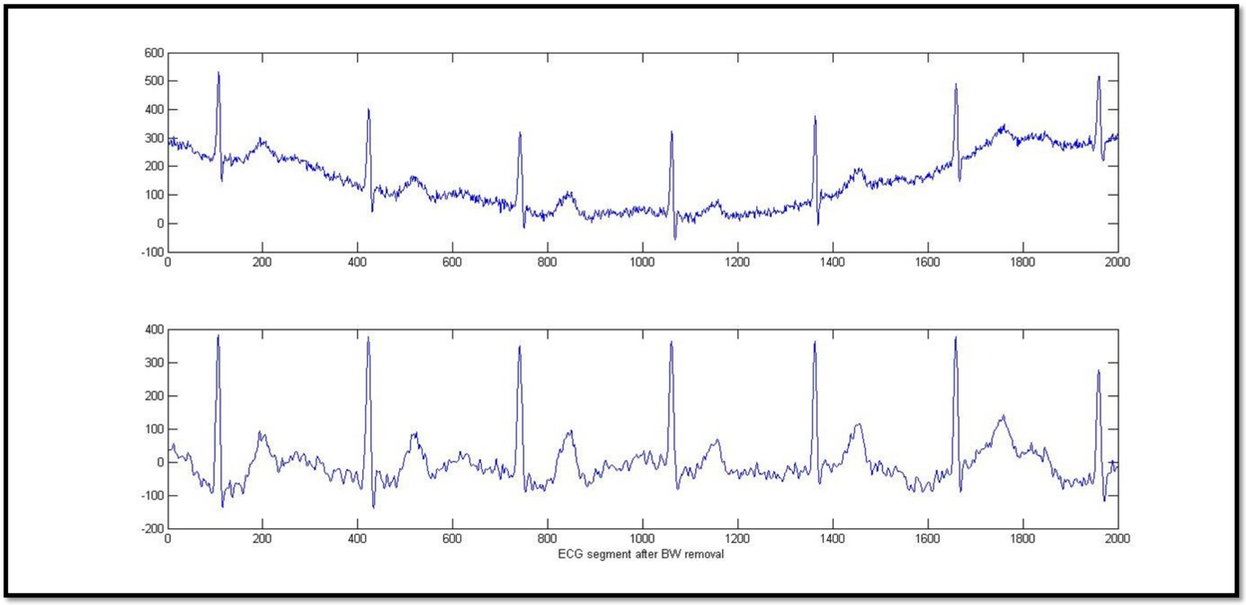


Figure 4.4: ECG segment: before and after BW correction

4.4.2 Example 2

This example demonstrate the removal of EMG noise from an ECG segment.

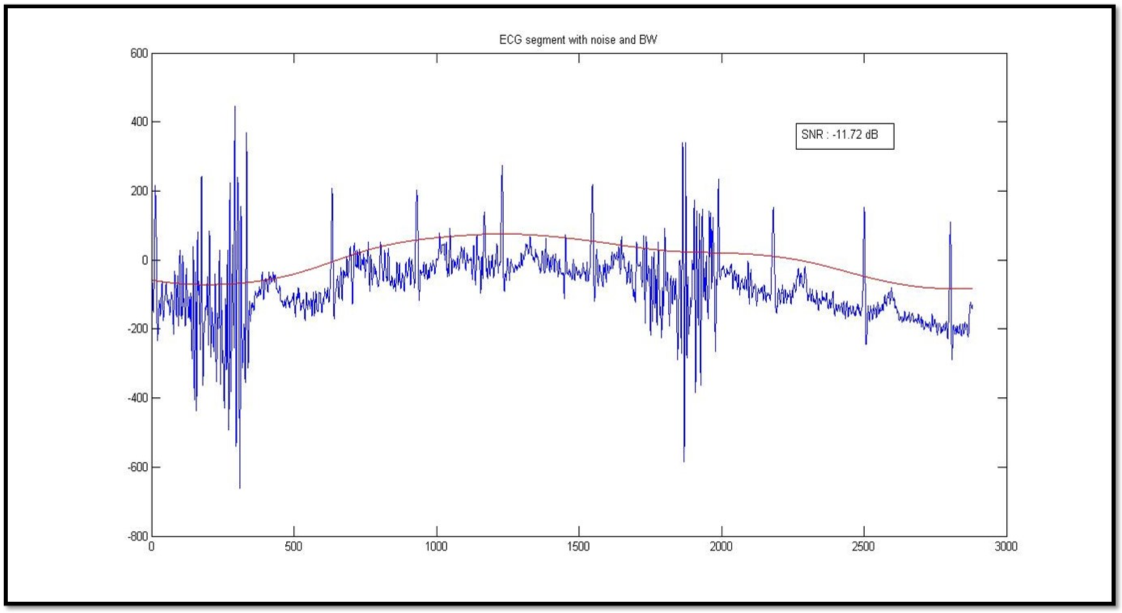


Figure 4.5: ECG segment with noise

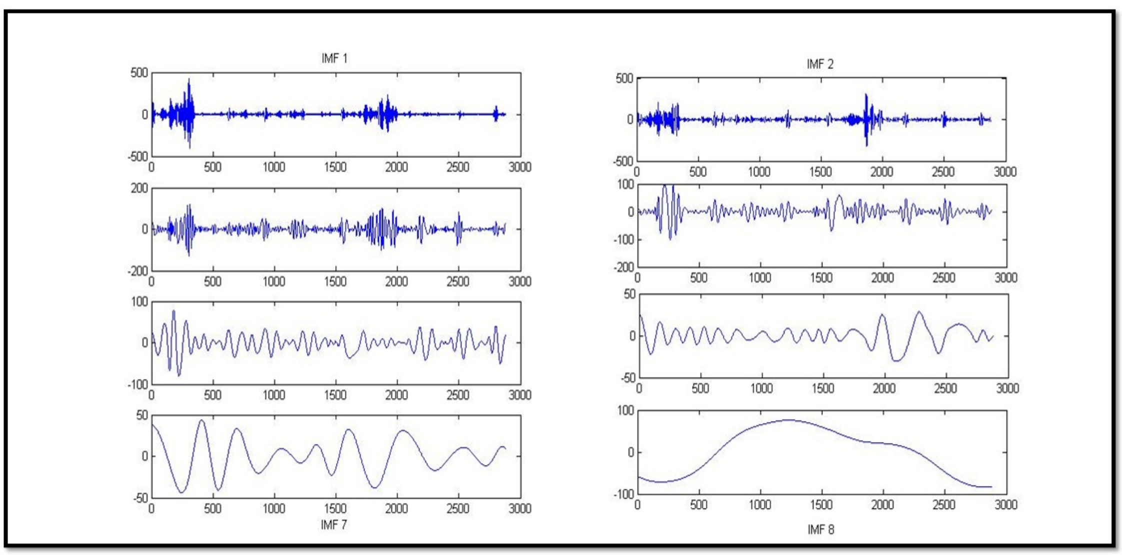


Figure 4.6: EMD of ECG segment with noise

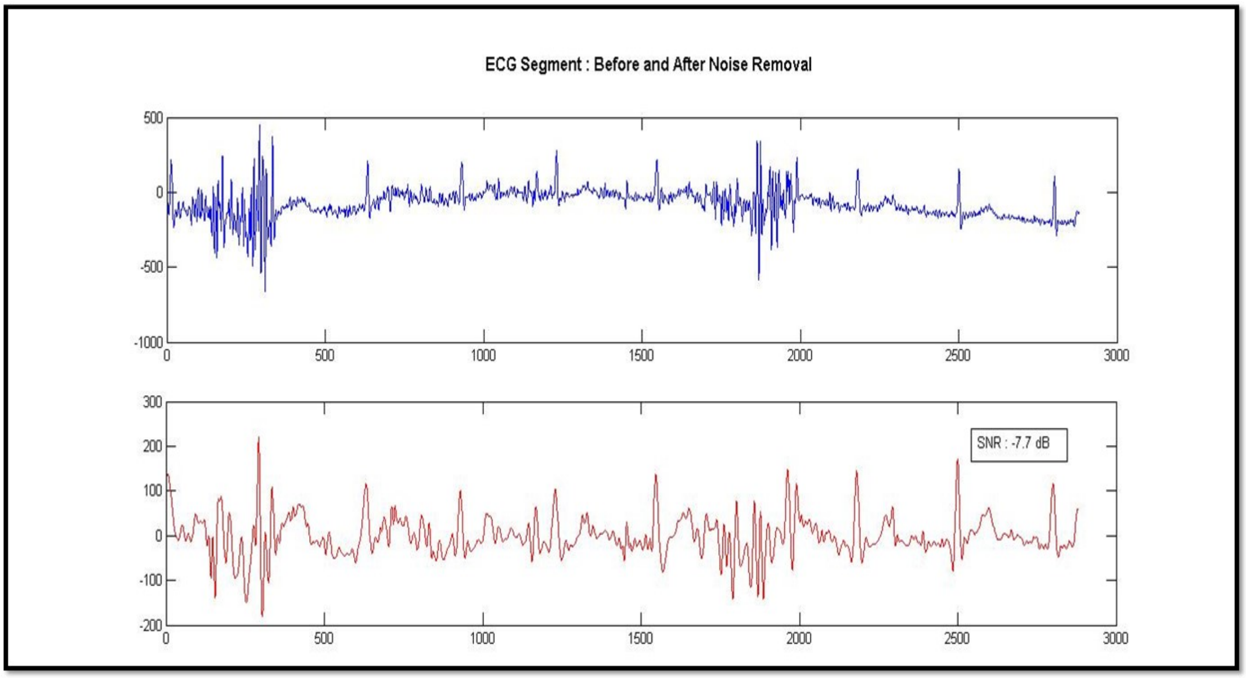


Figure 4.7: ECG segment : Before and after noise removal

Chapter 5

Conclusion

Conclusion

Suggestions for future work

Chapter 5

CONCLUSION

This chapter focuses on the performance analysis and limitations of the method used for signal denoising. The scope of future work in this field is also discussed.

5.1 Conclusion

The empirical mode decomposition allows successful denoising of the non- stationary electrocardiography signals. In the present thesis a new relationship to remove the noise from ecg signals has been proposed. A nosiy signal can be viewed as a summation of a finite set of IMFs which represent oscillatory modes hidden the data. The signal corruting noisy part is captured in the first few IMFs whereas slower variation like BW(baseline wander) is traped in higher order IMF. The EMD based methods are able to separate both the high and low frequency parts of any complex signal. Those IMFs which captures noisy components can be excluded from the reconstruction process. Thus by eliminating the undesired portions of the signals , denoising is achieved.Experimental testing of the new proposed method has been performed on different electrocardiogram signals **(MIT-BIH ECG Database)** to verify the described algorithm.

The obtained results show that the proposed scheme is suitable for ECG denoising with significent improvement in signal quality.Since Mathematical theory of EMD is yet to be finished but its performance is comparable with methods such as wavelet thresholding based methods.

5.2 Suggestions for Future Work

Various algorithmic improvements about EMD is proposed and need to be validated. EMD is a powerful technique for analysing a signal thus it can be combined with other methods such as wavelet tranform, ICA and PCA based methods to enhance its capbility of signal analysis.

Bibliography

[1] S. L. Joshi, R. A. Vatti, and R. V. Tornekar, "A survey on ecg signal denoising techniques," in *Communication Systems and Network Technologies (CSNT), 2013 International Conference on*. IEEE, 2013, pp. 60–64.

[2] F. Gritzali, G. Frangakis, and G. Papakonstantinou, "Noise estimation in ecg signals," in *Proceedings of the Annual International Conference of the IEEE ,Engineering in Medicine and Biology Society, 1988*. IEEE, 1988, pp. 152–153.

[3] M. Khan, F. Aslam, T. Zaidi, and S. A. Khan, "Wavelet based ecg denoising using signal-noise residue method," in *Bioinformatics and Biomedical Engineering,(iCBBE) 2011 5th International Conference on*. IEEE, 2011, pp. 1–4.

[4] B.-K. Ling, C.-F. Ho, H.-K. Lam, T.-L. Wong, A.-P. Chan, and P. K.-S. Tam, "Fuzzy rule based multiwavelet ecg signal denoising," in *Fuzzy Systems, 2008. FUZZ-IEEE 2008.(IEEE World Congress on Computational Intelligence). IEEE International Conference on*. IEEE, 2008, pp. 1064–1068.

[5] M. Blanco-Velasco, B. Weng, and K. E. Barner, "Ecg signal denoising and baseline wander correction based on the empirical mode decomposition," *Computers in biology and medicine*, vol. 38, no. 1, pp. 1–13, 2008.

[6] P. Mithun, P. C. Pandey, T. Sebastian, P. Mishra, and V. K. Pandey, "Awavelet based technique for suppression of emg noise and motion artifact in ambu-

latory ecg," in *Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE*. IEEE, 2011, pp. 7087–7090.

[7] D. Zhang, "Wavelet approach for ecg baseline wander correction and noise reduction," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*. IEEE, 2005, pp. 1212–1215.

[8] W. Zhang, X. Wang, L. Ge, and Z. Zhang, "Noise reduction in ecg signal based on adaptive wavelet transform," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*. IEEE, 2006, pp. 2699–2702.

[9] M. A. Kabir and C. Shahnaz, "Denoising of ecg signals based on noise reduction algorithms in emd and wavelet domains," *Biomedical Signal Processing and Control*, vol. 7, no. 5, pp. 481–489, 2012.

[10] C. Saritha, V. Sukanya, and Y. N. Murthy, "Ecg signal analysis using wavelet transforms," *Bulg. J. Phys*, vol. 35, no. 1, pp. 68–77, 2008.

[11] G. Garg, S. Gupta, V. Singh, J. Gupta, and A. Mittal, "Identification of optimal wavelet-based algorithm for removal of power line interferences in ecg signals," in *Power Electronics (IICPE), 2010 India International Conference on*. IEEE, 2011, pp. 1–5.

[12] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N.-C. Yen, C. C. Tung, and H. H. Liu, "The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis," in *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, vol. 454, no. 1971. The Royal Society, 1998, pp. 903–995.

[13] N. E. Huang and S. S. Shen, *Hilbert-Huang transform and its applications*. World Scientific, 2005, vol. 5.

[14] M. E. Torres, M. A. Colominas, G. Schlotthauer, and P. Flandrin, "Acomplete ensemble empirical mode decomposition with adaptive noise," in *Acoustics, Speech and Signal Processing (ICASSP), 2011 IEEE International Conference on*. IEEE, 2011, pp. 4144–4147.

[15] C.-K. Peng, S. V. Buldyrev, S. Havlin, M. Simons, H. E. Stanley, and A. L. Goldberger, "Mosaic organization of dna nucleotides," *Physical Review E*, vol. 49, no. 2, p. 1685, 1994.

[16] A. Mert and A. Akan, "Detrended fluctuation analysis for empirical mode decomposition based denoising," in *Signal Processing Conference (EUSIPCO), 2013 Proceedings of the 22nd European*. IEEE, 2014, pp. 1212–1216.

[17] P. Flandrin, P. Gonçalves, G. Rilling *et al.*, *Detrending and denoising with empirical mode decompositions*. Citeseer, 2004.

[18] R. Hardstone, S.-S. Poil, G. Schiavone, R. Jansen, V. V. Nikulin, H. D. Mansvelder, and K. Linkenkaer-Hansen, "Detrended fluctuation analysis: a scale-free view on neuronal oscillations," *Frontiers in physiology*, vol. 3, 2012.

[19] G. Rilling, P. Flandrin, P. Goncalves *et al.*, "On empirical mode decomposition and its algorithms," in *IEEE-EURASIP workshop on nonlinear signal and image processing*, vol. 3. NSIP-03, Grado (I), 2003, pp. 8–11.