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IMF And Filtering Based Denoising of ECG Signal

Aswathy Velayudhan, Soniya Peter

M.Tech Student [Communication Engg.], Dept. of ECE, SNGCE, Kadayiruppu, Kerala, India

Assistant Professor, Dept. of ECE, SNGCE, Kadayiruppu, Kerala, India

ABSTRACT: ECG Signal provides useful information about the state of heart. And the efficiency of diagnosis depends on the accurate analysis of ECG signal. However ECG signals are corrupted by many noises. For the proper diagnosis of the heart, the ECG signal must be free of noises. Several methods have been developed for ECG Signal denoising. In this paper a new ECG denoising method based on Empirical Mode Decomposition (EMD), Moving average filter and Discrete Wavelet Transform (DWT) is proposed. Simulations are carried out using the MIT-BIH database and the performances are evaluated in terms of standard metrics namely, SNR improvement in dB, Mean Square Error (MSE) and Percent Root Mean Square Difference (PRD). The results show that the proposed method provides very good results for denoising of ECG Signal.

KEYWORDS: Electrocardiogram (ECG), Denoising techniques, Empirical mode decomposition (EMD), DWT, Mean Square Error (MSE) and Percent Root Mean Square Difference (PRD)

I. INTRODUCTION

Electrocardiogram (ECG) is a diagnostic tool that measures and records the electrical activity of the heart. A typical ECG tracing of a normal heartbeat (or cardiac cycle) consists of a P wave, a QRS complex and a T wave. A small U wave is normally visible in 50 to 75% of ECGs. Normally, the frequency range of an ECG signal is of 0.05–100 Hz and its dynamic range of 1–10 mV. The P-wave represents the activation of the upper chambers of the heart, the atria, while the QRS complex and T-wave represent the excitation of the ventricles or the lower chamber of the heart. Normal ECG signal is represented in figure 1. An ECG conveys a large amount of information about the structure of the heart and the function of its electrical conduction system to the trained clinician.

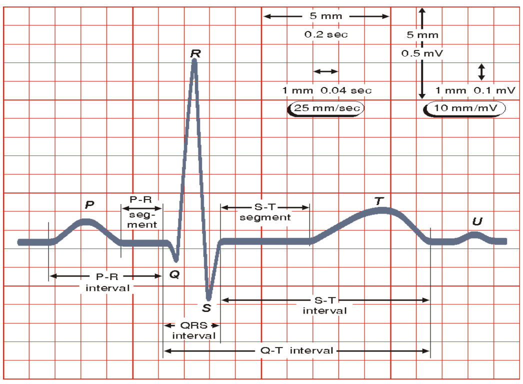

Fig 1. Normal ECG signal

Different noises are corrupted with ECG signal during its acquisition and transmission. Mainly two types of noises that get contaminated with ECG signal that are high frequency signal and low frequency noises. High frequency noise that includes Electromyogram noise (EMG) - caused due to electrical activity of muscle, motion artifacts - caused due

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to motion of electrode, channel noise - White Gaussian Noise introduced during transmission through channels, and power line interferences and the low frequency noise include baseline wandering due to respiration or coughing. The noisy ECG signal is represented in figure 2.

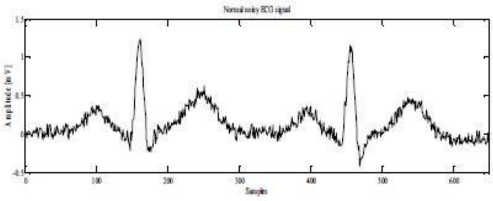

Fig.2. Human's ECG Signal: Normal noisy ECG [1]

Noises need to be attenuated in order to obtain a clean ECG signal for accurate diagnosis of heart condition.

II. RELATED WORK

In [2] authors used a fast algorithm for detecting EMG noise and it uses a morphological filter to detect and filter the EMG noised ECG signal. The morphological filter, filtered the unwanted shapes of the signal while the other parts of signal being unchanged. In this algorithm first the EMG noise is extracted (separated) from the ECG signal. Then the QRS complexes are located and it suppressed. Moving variance of the signal is calculated by using a standard variance formula. Sections of EMG noise can be identified by setting a threshold on the calculated moving variance. This algorithm has an advantage that it has low computational complexity such that it can apply in massive ECG collections. The limitation is that the morphological filter has fixed coefficients that may have little difficult to apply to the biomedical signal like ECG signal. In [3] authors introduced an adaptive filtering algorithm to denoise the ECG signal .That is adaptive filters are used to reduce the ECG signal noises like PLI and Base Line Interference. Here Recursive least squares (RLS) algorithm is used and an Adaptive Noise canceller to denoise the ECG signal. RLS algorithm is really effective in clinical situations; the method has been validated using several ECG recordings with a wide variety of wave morphologies from MIT-BIH arrhythmia database. An advantage of this technique is that it has fast convergence even when the Eigen value spread of the input signal correlation matrix is large. The limitation is that it has high computational complexity and some stability problems. In [4] authors through their paper discussed wavelet based wiener filter for ECG signal denoising.The frequency spectrum of the ECG signal contains the components approximately from 1 to 125 Hz. Frequency spectrum of the myopotentials is sharply overlapped with spectrum of the ECG signal. Discrete-time wavelet transform (DTWT) appears as a useful tool for myopotentials suppression. Here Wavelet domain Wiener filtering with pilot estimation of the signal is done. In wavelet domain Wiener filtering with pilot estimation. At first the input signal is decomposed by DTWT (WT1) into 4 levels. Then the coefficients are thresholded and reconstructed by inverse DTWT. Output of this configuration gives the pilot estimation of the signal. This technique has an advantage that it does not distort the extremes in QRS complexes. A new method for ECG denoising based on the Empirical Mode Decomposition (EMD) was proposed in [5].The EMD technique does not require any priori knowledge of the signal.EMD is an adaptive, high efficient decomposition technique in which any complicated signal can be decomposed into finite number of Intrinsic Mode functions (IMFs). The IMFs represent the oscillatory modes embedded in the signal. Denoising in the EMD is usually done by discarding lower-order IMFs by assuming that the signal and noise are well-separated in frequency bands [5]. In this EMD based technique the signal to error ratio (SER) improves when signal to error ratio (SNR) increases.

III. PROPOSED METHOD

Here, in order to preserve the QRS information in the presence of noise, the noisy ECG signal is first enhanced in the EMD domain by a windowing operation and the smoothened by a moving average filter. Then, the ECG signal with

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a relatively reduced noise is transformed in the wavelet domain. Finally, wavelet soft thresholding scheme is employed to the wavelet coefficients prior to reconstructing a cleaner ECG signal.

A. ECG signal Denoising-Block Diagram

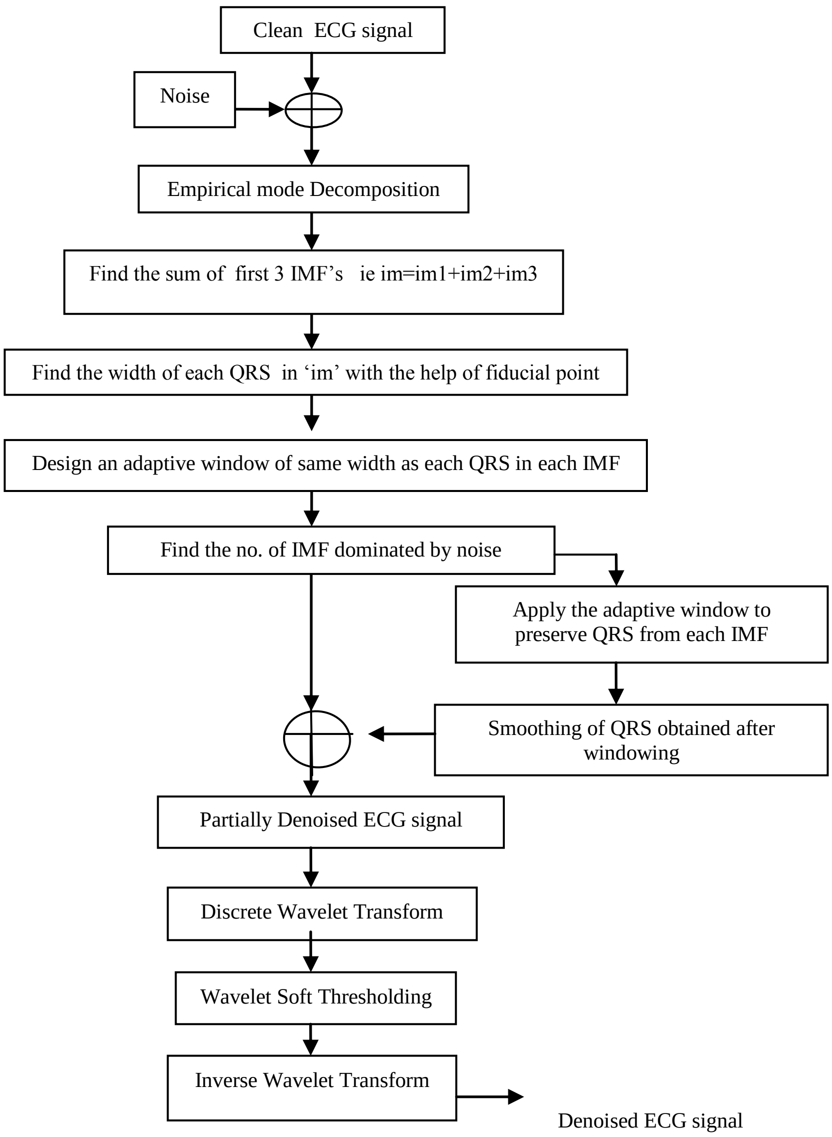

Fig 3.Block diagram of proposed method

The basic steps involved in the proposed denoising method includes addition of Additive white Gaussian noise (AWGN) to a clean ECG signal to get noisy ECG signal. Using empirical mode decomposition (EMD) and moving average filtering technique, the ECG signal is partially denoised. For further reduction of noise the signal is transformed in to wavelet domain, here discrete wavelet transform is done.Figure 3 represents the block diagram of proposed method.

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B. Empirical Mode Decomposition

The first step in denoising of ECG signal is Decomposition of noisy ECG signal in to intrinsic mode functions (IMFs). For this Empirical mode decomposition (EMD) is applied to the noisy ECG signal. EMD is a flourishing method for analysing nonlinear and non-stationary data by decomposing them into a finite and often small number of "intrinsic mode functions" that must follow two conditions:

1. The no of local extrema and the zero crossing must be equal or differ by at most one.
2. At any point of the time, the mean value of the upper envelope (local maxima) and the lower envelope (local minima) must be zero [6].

The process of extract the IMFs is called the Sifting Process and is consists of the following steps:

1. Identify all the extrema of noisy ECG signal x(t).
2. 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.
3. Compute the mean $m(t)$ and it is given as

$$m(t) = {[u(x) + l(x)]}/{2} \qquad \dots eq\ (1)$$

Where $m(t)$ is the mean of the upper envelope $u(x)$ and lower envelope $l(x)$

4. Extract the component $h(t)$. And it is the difference between the noisy ECG signal and the mean. And it is the proto IMF $h(t)$

$$h(t) = x(t) - m(t) \qquad \dots eq(2)$$

5. Check the proto-IMF against the definition of IMF and the stoppage criterion to determine if it is an IMF.

6. If the proto-IMF does not satisfy the definition, repeat step 1 to 5 on $h(t)$ as many time as needed till it satisfies the definition.

7. If the proto-IMF does satisfy the definition, assign the proto-IMF as an IMF component, $c(t)$.

8. Repeat the operation step 1 to 7 on the residue, $r(t) = x(t) - c(t)$as the data.

9. The operation ends when the residue contains no more than one extreme.

We can stop the sifting process by limiting the sum of difference (SD).
The SD is defined as ;

$$SD = \sum_{t=0}^{T} \left[\frac{\left| h_{1(k-1)}(t) - h_{1k}(t) \right|^2}{h_{1(k-1)}^2(t)} \right] \qquad \dots eq(3)$$

C. Finding the Width of QRS complex And Window design

To preserve the QRS complex we must find the Width of the QRS complex and it can be found by following steps:

1. Identification of the R-peaks
2. Addition of 1st 3 IMFs to get 'im' after applying EMD to the noisy ECG signal
3. Finding of two local absolute minima on both sides of the fiducial points
4. Detection of the zero crossing points on the LHS of the left absolute minima and on the RHS of the right absolute minima [6]

An adaptive window is designed to preserve the QRS complex. Here Tukey window (Tapered cosine window) is designed.

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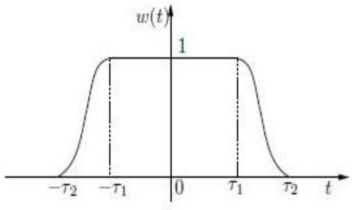

Fig 4.Tukey Window [5]

The window function is given as;

$$w(t) = \begin{cases} \frac{1}{2}\left[1 + cos\left(\pi \frac{|t| - t_1}{t_2 - t_1}\right)\right] & ;\ t_1 \leq |t| \leq t_2 \\ 1 & ; |t| < t_1 \\ 0 & ; |t| > t_2 \end{cases} \qquad \ldots eq(4)$$

Where t_1 is the flat region limit and t_2 is the transition region limit. By using eqn (4), the flat region width 2 $t1$ is chosen such that it equals the QRS complex width. The spread around the QRS complex increases with the IMF order. A variable width transition region in eqn (4) is adopted to cope with the spreading effect of the various IMFs. Define the ratio between the one-sided transition region length $|t1 - t2|$ and the flat region length 2 $t1$ as α

$$\alpha = |t1 - t2|/2t1 \qquad \ldots eq(5)$$

Where α is a free parameter [5]

D. Finding the number of noisy IMFs And preservation of QRS complex

The statistical t test is used to find the number of noisy IMFs. Two hypothesis of t-test i.e, null hypothesis and alternative hypothesis testing can be used here for finding the number of noisy IMFs as follows:

$$\left.\begin{array}{l} Ho: mean\left(H_{PS}^{N}(t)\right) = 0\ \ (null\ hypothesis) \\ H1: mean\left(H_{PS}^{N}(t)\right) \neq 0\ \ (alternative\ hypothesis) \end{array}\right\} \ldots eq(6)$$

Where, $H_{PS}^{N}(t)$ is the N^{th} order partial sum of the IMFs. To preserve the QRS complex the tapered cosine window is applied to these noisy IMFs. On applying this window function to all the noisy IMFs, only QRS width will be preserved and other than this everywhere we will get a sharp change to zero. To avoid this sudden change and to preserve the remaining information, we applied a complementary window to these noisy IMFs with a very less attenuation factor [6]

E. Smoothening of QRS complex And Reconstruction of partially denoised ECG signal

After adding the windowed IMFs together, smoothening is done. Smoothening is done using moving average filter. The moving average filter is a simple Low Pass FIR (Finite Impulse Response) filter. Here moving average technique with a span of 3 is used that is it will smooth the signal (here mainly QRS complex) by taking the average of its three neighbouring samples. And then by adding the smoothed windowed signal, Complimentary windowed IMFs, Remaining non noisy IMFs and Residual we get the partially denoised ECG signal.

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F. Decomposition in Wavelet domain

The partially denoised signal $\tilde{x}(n)$ can be expressed as

$$\tilde{x}(n) = x(n) + \tilde{v}(n) \qquad \ldots eq(7)$$

Where,

$x(n)$ is the original clean ECG signal and $\tilde{v}(n)$is the additive noise remaining after EMD and moving average filter operation. Wavelet transform of $\tilde{x}(n)$ is done up to a chosen level. If W denotes the wavelet transform then equation (7) can be written in the wavelet domain as

$$\tilde{X} = X + \tilde{V} \qquad \ldots eq(8)$$

Where,

$\tilde{X} = W\tilde{x}(n)$, $\tilde{V} = W\tilde{v}(n)$, $X = Wx(n)$. By using DWT $\tilde{x}(n)$ signal is decomposed in to DWT coefficients.

G. Thresholding in the wavelet domain

After decomposition of $\tilde{x}(n)$ signal in to DWT coefficients, thresholding must be done. By performing thresholding operation on $\tilde{X}$, we can estimate the denoised ECG signal as

$$\hat{X} = THR(\tilde{X}, \delta) \qquad \ldots eq(9)$$

Where $THR(.)$ denotes the thresholding function and δ denotes the threshold value. Normally the value of δ is given by,

$$\delta = \sigma\sqrt{2logM} \qquad \ldots eq(10)$$

Here, σ is the standard deviation of the detailed DWT coefficients of a wavelet level and M is the length of the vector of the DWT coefficients. After the determination of δ, thresholding is done. There are two types of thresholding methods are present, wavelet hard thresholding and wavelet soft thresholding. Wavelet soft thresholding is used here.
In soft thresholding, signal values smaller than δ are turned to zero and is subtracted from the signal values greater than δ. In equation form the thresholding operation performed on a particular detailed DWT coefficient on a wavelet level can be expressed as,

$$\widehat{X_{di}}\,(l) = \begin{cases} \left|\widetilde{X_{di}}\,(l)\,\right| - \delta_l \;, \left|\widetilde{X_{di}}\,(l)\right| \geq \delta_l \\ \quad 0 \quad , \qquad \left|\widetilde{X_{di}}\,(l)\right| < \delta_l \end{cases} \ldots eq(11)$$

Where, i stands for the index of the detailed DWT coefficients at level l. In contrast to hard thresholding, soft thresholding causes no discontinuities in the resulting signal.

H. Reconstruction of the ECG signal

Finally obtain the estimate of original ECG signal $\hat{x}(n)$ by using inverse wavelet transform on $\hat{X}$ as given by

$$\hat{x}(n) = IDWT\left[\hat{X}\right] \qquad \ldots\; eq(12)$$

Where, $IDWT$ represents an inverse DWT operation. The noise is further reduced in the proposed method than the EMD and moving average filtering technique (existing method).

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IV. SIMULATION RESULTS

A. Database and other simulation details

Matlab R2007b is used as the simulation tool. The various ECG signals were taken from the MIT-BIH arrhythmia database and the additive white Gaussian noise of 12 dB SNR was added to them for the testing of the proposed algorithm. In the denoising of the ECG signal, the EMD was applied to the noisy ECG signal, then the number of noisy IMFs were calculated and found to be five by the statistical t-test for a significance level of 5%. The transition parameter α is set here as 30% in the window function, since the numbers of noisy IMFs were found as five thus the attenuation coefficient was set to 0.10, 0.15, 0.20 0.25,0.3 for the 1st to 5th IMFs respectively for the complementary window. Haar wavelet is selected as the mother wavelet. A 3-level decomposition of DWT is done. Whole algorithm was simulated in the MATLAB.

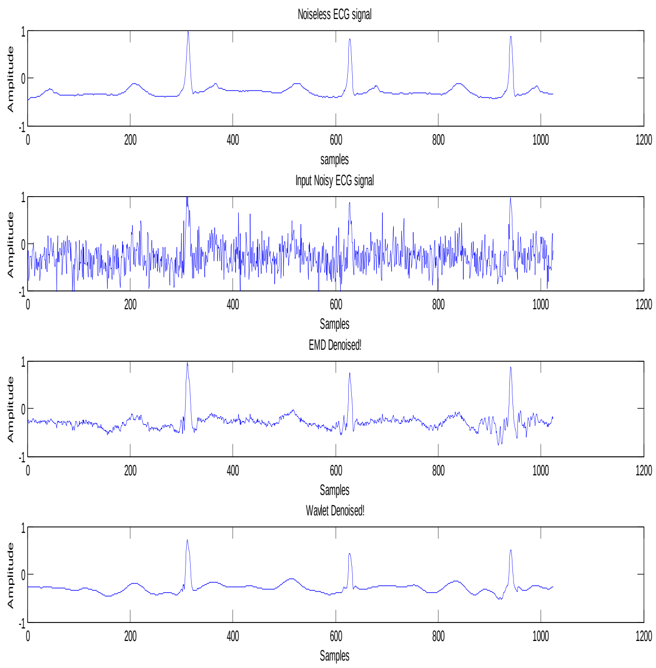

Figure 5. Denoised ECG signal using existing method and proposed method

Figure 5 shows that the Empirical mode Decomposition (EMD) and moving average filtering denoising technique (Existing method) reduce noise partially, that is large amount of noise content still exists in the ECG signal. IMF and filtering based denoised method (proposed method) reduce noise more effectively than the existing method.

B. Performance evaluation and comparison

The performance of the proposed method is evaluated with the existing Empirical mode decomposition and moving average filtering method. Simulations are carried out in MATLAB R2007b environment. The performance of the proposed method compared with other based on 3 parameters: improvement in signal to noise ratio (SNR_{imp}), mean square error (MSE), and percent root mean square difference (PRD). The parameters are computed as follows

1) Signal to noise ratio improvement (SNR imp)

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$$SNR_{imp}\,[dB] = 10log_{10} \frac{\sum_{n=1}^{N} |y[n] - x[n]|^2}{\sum_{i=1}^{N} |\hat{x}\,[n] - x[n]|^2} \qquad \ldots eq(13)$$

2). Mean square error (MSE)

$$MSE = \frac{1}{N} \sum_{n=1}^{N} (\,x[n] - \hat{x}\,[n]\,)^2 \qquad \ldots eq\ \ (14)$$

3). Percentage Root mean square Difference (PRD)

$$PRD = \sqrt{\frac{\sum_{n=1}^{N} (x[n] - \hat{x}[n])^2}{\sum_{i=1}^{N} x^2[n]}} \times 100 \qquad \ldots eq(15)$$

Where,

$x[n]$ —— Clean ECG signal

$y[n]$—— Noisy ECG signal and

$\hat{x}\,[n]$ —— Reconstructed ECG signal using Denoising techniques.

N —— Number of ECG samples.

For a denoising method to be said better, SNR imp should be larger , MSE and PRD should be smaller.

Table 1 shows the results of improvement in signal to noise ratio (SNR_{imp}), mean square error (MSE), and percent root mean square difference (PRD) of different ECG recordings numbered as 100,103.119,213 for the existing method (Empirical mode decomposition and moving average filter denoising method) and proposed method(IMF and filtering based method).From the table it is observed that the SNR_{imp} is higher for proposed method for the ECG recordings 100,103,119 and 213. And the mean square error (MSE), and percent root mean square difference (PRD) is lower when compared with the existing method. From the table it is clear that the proposed method is a good and efficient method to denoise the ECG signal because of its high SNR_{imp} and low , PRD values.

Table 1.Resultant of SNRimp, MSE, PRD of Existing and Proposed Method

ECG Record	Denoising Technique	$SNR_{imp}\,[dB]$	MSE	PRD
100	EMD + moving average method	6.5711	0.0124	28.7359
	Proposed method	7.3576	0.0104	26.2481
103	EMD + moving average method	9.2125	0.0082	27.8005
	Proposed method	10.7316	0.0058	23.3399
119	EMD + moving average method	6.8356	0.0117	10.2576
	Proposed method	8.2187	0.0085	8.7476

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213	EMD + moving average method	7.7520	0.0114	30.0634
	Proposed method	9.4201	0.0078	24.8104

V. CONCLUSION

An effective method of ECG signal denoising based on Empirical mode Decomposition, Moving average filter and discrete wavelet Transform is presented. In order to discard noise mainly existing in the initial IMFs , we apply a tukey window (tapered cosine window) in the EMD domain and a moving average filter for smoothening purpose. A wavelet soft thresholding is performed in the DWT domain for further reduction of the noise remaining after EMD and moving average filtering operation. EMD and DWT domain based denoising methods reduce noise from ECG signals more effectively compared to conventional signal enhancing algorithms. The proposed method is compared with the existing method in terms of three parameters: improvement in signal to noise ratio (SNR_{imp}), mean square error (MSE) and percent root mean square difference (PRD). From the comparisons made it can be understood that the proposed method is better than the existing method.

REFERENCES

1. Omid Sayadi , Mohammad Bagher Shamsollahi, "ECG Denoising with Adaptive Bionic Wavelet Transform" , in Proceedings of the 28th IEEE EMBS Annual International Conference New York City, USA, Aug 30- Sept 3, 2006
2. P. Raphisak, S.C. Schuckers, A.J. Curry, An algorithm for EMG noise detection in large ECG data, Comput. Cardiol, 31 (2004) 369–372.
3. Chinmay Chandrakar, M.K. Kowar, "DENOISING ECG SIGNALS USING ADAPTIVE FILTER ALGORITHM", International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-2,Issue-1, March 2012
4. Chmelka, J Kozumpl´ık, "Wavelet-Based Wiener Filter for Electrocardiogram Signal Denoising", IEEE 2005,Computers in Cardiology 2005;32:771−774
5. B. Weng, M. B. Velasco, and K. E. Barner, "ECG denoising based on the empirical mode decomposition," in Proceedings of the 28th IEEE EMBS Annual International Conference New York City, USA, Sept.2006, pp. 1–4.
6. Sonali, Omkar Singh, Ramesh Kumar Sunkaria- ECG Signal Denoising Based on Empirical Mode Decomposition and Moving Average Filter, 2013 IEEE
7. The MIT-BIH noise stress test database. [Online]. Available: http://www.physionet.org/physiobank/database/nstdb/.
8. MIT-BIH arrhythmia data base [Online]. Availabile at :http://www.physionet.org/physiobank/database/mitdb/
9. Matlab help, MATLAB MATHWORKS. [Online]. Available:http://www mathworks.com

BIOGRAPHY

Aswathy Velayudhan received B. Tech degree in Electronics and Communication Engineering from Mahatma Gandhi University, Kerala, India in 2012. Currently pursuing M.Tech in Communication Engineering from Mahatma Gandhi University, Kottayam, Kerala, India. Area of interests includes Communication Engineering and Signal Processing

Soniya Peter, Assistant Professor in the Department of Electronics and Communication Engineering, SNGCE. Secured M.Tech in Signal Processing from Rajagiri School of Engineering and Technology, Mahatma Gandhi University and B.Tech in ECE from Mahatma Gandhi University, Kottayam. Working areas includes Signal Processing and Array Processing.