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Removal of Artifcats in Electrocardiograms using Savitzky-Golay Filter: An Improved Approach

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Abstract

Electrocardiogram (ECG) is a tool used for the electrical analysis of the status of human heart activity. When the ECG signal is recorded, it gets contaminated with different types of noises. So, for accurate analysis, noises must be eliminated from the ECG signal. There are different types of noises that contaminate the characteristics of ECG signal i.e Power line interference, baseline wander, Electromyogram (EMG). In this paper, different techniques have implemented for the removal of noises. A median filter is used for removal of DC component and Savitzky-Golay filter (SG) is used for smoothing noised waveform and then wavelet transform (db4) is used to decompose the ECG signal for removal of various artifacts. Wavelet transform provides the information in frequency and time domain and then thresholding has been applied for the implementation of algorithms in MATLAB. The measured results i.e. SNR(Signal to Noise ratio) and MSE(Mean square error) have been calculated using different databases like MIT-BIH, Long-term ST database, European ST-T database. The results are examined with proposed methods that are better than those reported in the literature.

Keywords: Base line wander, ECG, EMG, MSE (Mean square error), Power line interference, Savitzky-Golay filter, Signal to Noise Ratio (SNR), Wavelet transform.

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Introduction

ECG is a method used for the proper detection of diseases related to heart that is the primary cause of death all over the world. It represents the electrical activity of the heart in the form of a scanned image. ECG can be employed for recording purposes (Patil, 2015). ECG waveform comprises different types of components P, QRS complex, T waveform. A ----typical ECG waveform is shown in figure 1. Today, the biggest challenge is to analyses the ECG signal with accuracy and precision. Because while recording the ECG signal, it is contaminated with many noises (Pater, 2005). Many filters, algorithms, etc. are developed by the researchers but research is still going on for achieving accurate and best results (Sangaiah et al., 2019).

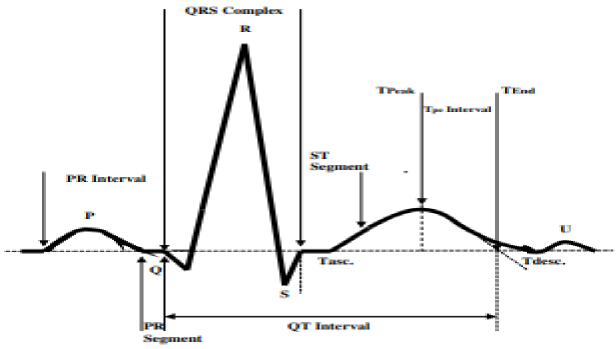


Figure 1. Components of ECG waveform

Noises are the undesired form of signals that occurred while recording ECG signals and it hinders the correct analysis by the specialist. So, it is very necessary to eliminate these noises from the original signal using a method i.e. preprocessing (Oussama et al., 2017). Different types of artifacts take place in ECG signals like baseline wander, power line interference, and EMG. The baseline wander is a type of artifact, having a very low frequency that is generated during recording from body movement. It displaced the level of ECG from a zero baseline that makes it very difficult to estimate the low frequency. So, this is saturated by using a median filter and if the ECG signal does not come at zero levels it shows the presence of low frequency which is further removed by the Savitzky-Golay (SG) filter (Pal and Mitra, 2012). PLI (Power line interference) occurs due to electromagnetic interference of frequency 50 Hz/60 Hz. It is generated due to low channel conditions and is removed by using a notch filter. The different techniques are used for the analysis of the ECG signal. In this paper, comparisons between different databases have been done. Measured results are shown in table in terms of SNR, MSE etc.The latest technology used for the analysis and detection of heart diseases that reduce the burden on the specialist and provides life to heart patients (Sangaiah et al., 2019). An algorithm based on an adaptive tunable notch filter is presented in ref (Verma and Singh, 2015) for the reduction of high noise from heart activity. For the enhancement of ECG signal, authors proposed a technique based on Stock Well Transform in (Ariet al., 2013).

EMD and fractal-based techniques can be employed for the elimination of PLI and baseline wander artifacts from the electrocardiogram (ECG) signal in (Agrawal and Gupta, 2013). In (Wang et al., 2015), the authors proposed a filter based with zero phase technique for the elimination of noise from electrocardiogram (ECG) signal. In (Poungponsri and Yu, 2013), wavelet transforms, and artificial neural networks are proposed for suppression of noises in the ECG signal. In remote health care monitoring systems, the great importance of processing, and the analysis of biomedical signals is proposed in ref (Elgendi, 2018; Elgendi ,2018). For efficient detection of the ECG signal, a noise-tolerant ECG detector is designed, and a wearable ECG monitoring system is proposed (Izumi et al., 2015). In (Pareschi et al. ,2017), a compression-based algorithm is proposed for the reduction of data and consumption of power during transmission. In (Jain and Bhaumik,2017), for the detection of heart diseases on Smartphone and analysis of feature extraction, an efficient ECG signal processing is proposed. In (Hadji et al., 2016), a method is presented which is based on discrete wavelet transforms for removal of various noises i.e. power line interference, baseline wander, and EMG. In (Eminaga, 2018), a wavelet transforms and hybrid IIR/FIR filter is proposed for the removal of noises from the ECG signal. In (Wang et al., 2019), logistic regression and dual-tree complex wavelet transform is proposed for hearing loss identification for analysis of various heart diseases.

This paper covers the literature survey and research gap, and these research gaps give a direction to do work and objectives can be achieved. These are the research gap which is recently viewed by the authors according to literature. In this paper, the proposed work presents a new technique to resolve the problem of smoothing the noised waveform of electrocardiogram (ECG) signal. This paper explains the flow diagram for elimination of high frequency noise and low frequency noise. In this flow diagram, firstly load the ECG data from database and then sampled the data using down sampling process, after that one-stage median filter is used for removal of baseline wander and output of median filter is given to a new filter Savitzky-Golay (SG) for smoothing the noised waveform. After that wavelet transforms(db4) is used for elimination of high frequency noises present in electrocardiogram (ECG) signal. The baseline wander is a noise having very low frequency that is generated from the body movement during recording. So, it displaced the level of ECG signal from zero that makes it very difficult to estimate the low frequency. The proposed method is validated on standard database of European ST-T database, Long-term ST database and MIT-BIH database for different records and measured results in the form of Mean square error (MSE) and Signal to noise ratio (SNR), and compared these results with existing works. The results show that proposed method archived better SNR and less MSE than that reported in other literature. The paper has been divided into five sections: First section is introduction to ECG and also explains the noises in ECG signal, second section includes materials and methods, third section is simulated results and discussion, fourth section makes the comparison with state of art works and last section includes conclusions.

Noises in ECG Signal

- ***Baseline wander***

When baseline wander noise occurs in the ECG signal then the signal moves from zero base line. Due to this, the ECG signal changes the position from the iso-electric line. This noise is caused by the placement of improper electrodes, movement of patient and breathing. The adverse effect of this artifact in the electrocardiogram (ECG) signal leads to difficulties in the detection of the ECG signal. The frequency range of this noise is 0.5 to 0.6 Hz. Due to very low frequency; it is difficult to detect baseline wander (Kher, 2019). The electrocardiogram (ECG) signal with baseline wander is shown in figure 2.

Figure 2. Electrocardiogram (ECG) signal with baseline wander
(reproduced from http://www.mauvila.com/ECG/ecg_artifact.htm)

- ***Power Line Interference***

: This noise is caused by a stray electromagnetic field. PLI occurs in the frequency range of 50/60 Hz. This kind of noise occurred when the ECG machine is not properly equipped that makes analysis of the electrocardiogram (ECG) signal more difficult (Kher. R. ,2019). So, it is very important to eliminate this noise. If it does not removed, then it get superimposed on the ECG waveform components-like P and T wave as shown in figure 3.

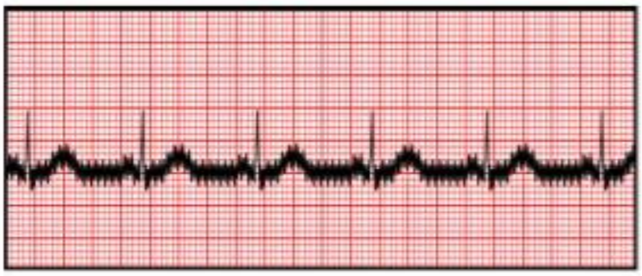


Figure 3. Electrocardiogram (ECG) signal with power line interference
reproduced from http://www.mauvila.com/ECG/ecg_artifact.htm

- ***Electromygram (EMG) Noise:***

This artifact occurs due to electrical activity of muscles. It creates a problem in the ECG signal during recording. It completely disappears the low amplitude waveform. It consists of a maximum frequency of 10 kHz. It is very difficult to minimize this noise because it cannot reduce by using narrowband filtering (Kher ,2019). If it is not removed, then it completely overlaps the PQRST complex as shown in figure 4.

Figure 4. Electrocardiogram (ECG) signal with Electromyogram (EMG) noise
reproduced from http://www.mauvila.com/ECG/ecg_artifact.htm

Materials and Methods

Various electrocardiogram (ECG) databases are presented for researchers to check their new proposed algorithm. These databases are annotated, and validated results have been generated. Then the doctors compare these results with the original signal. In this paper, authors used different databases i.e. MIT-BIH database and European ST-T database and Long-term ST database. In MIT-BIH database, sampling frequency is 360 Hz. This type of database comprises of 48 records and each record is having duration of half an hour. In above said database, the total numbers of beats are 110,007. European ST-T database comprises of 90 signals and each signal is having recording duration of two hours and each signal is sampled at frequency 250 Hz (Manocha. A. K, Singh. M. ,2015) whereas Long term ST database comprises of 86 signals and each record digitized at 250 samples per seconds with 12-bit resolution over a range of 10mv.The ECG signal from MIT-BIH database, European ST-T database and Long-term ST database are down sampled at sampling frequencies of 360Hz, 250Hz, and 250Hz. These signals are passed through median filter for the removal of baseline wander noise, further these signals pass through Savitzky-Goley(SG) filter for smoothing the noise waveform and then used wavelet transforms for removal of high frequency noise.

Methods

Firstly, load the ECG data from different databases, and then ECG signals are sampled using down sampling and then passed to the median filter for removal of baseline wander noise.

After that output of median filter is passed to Savitzky-Golay (SG) filter for smoothing of noise waveform and then wavelet transform (db4) has been employed to decompose the electrocardiogram (ECG) signal and eliminate the high frequency noises. The flow chart for removal of artifacts in ECG shown in figure (5).

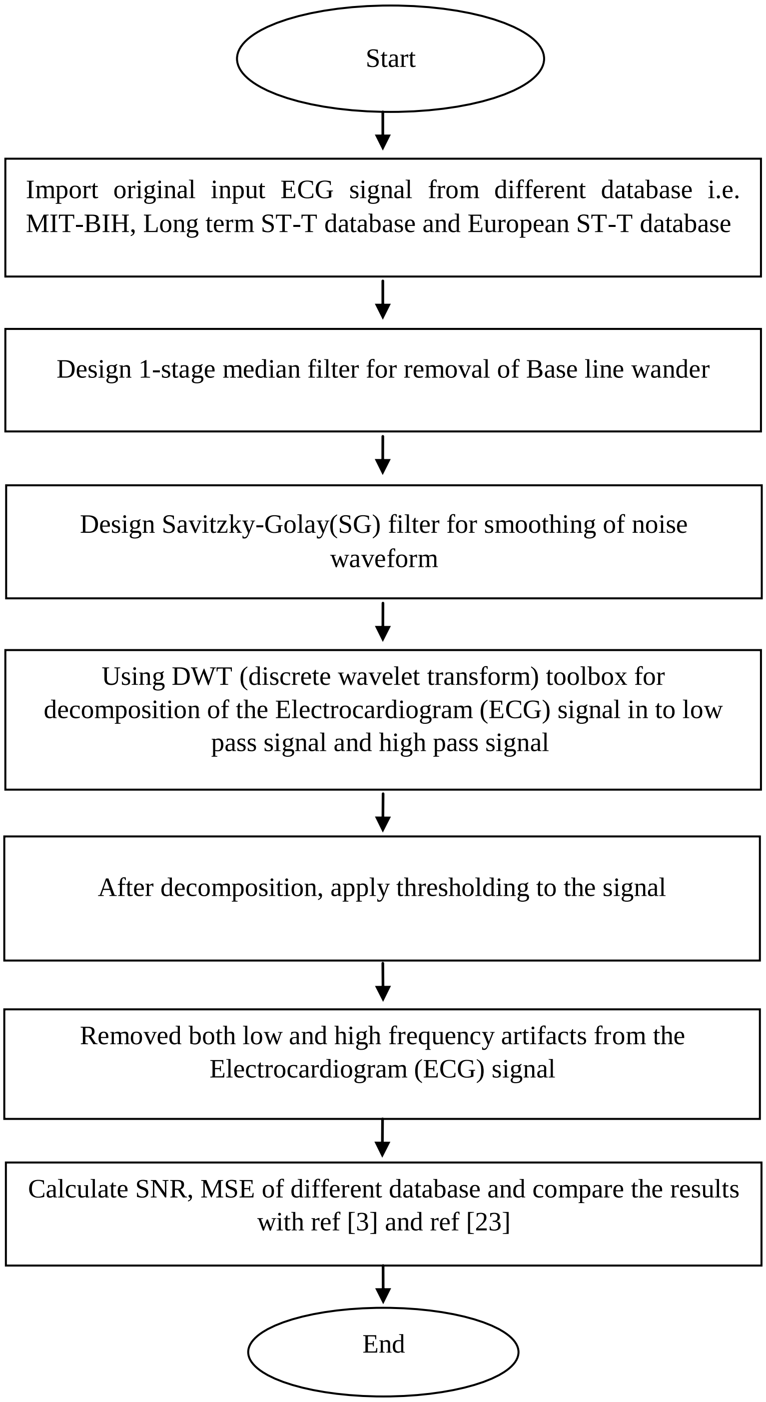


Figure 5. The flow chart for removal of artifacts in ECG

Wavelet Transform

The analysis of biomedical signals can be done in the time domain, frequency domain and both in the frequency-time domain. For data analysis, there are following transforms exists**:** Fourier Transform: It is employed for measuring the signal in terms of frequency. But it has disadvantage that its losses the important information in time domain (Manocha and Singh, 2015). When Fourier transform is applied to a signal, it is very difficult to predict a time when this event occurs. So, the solution of this problem is STFT (short time Fourier transform). In this, the signal is represented in terms of frequency and time. It is also known as frequency–time analysis of non-stationary signal. In STFT the signal is decomposed into small signal by multiplication with window. But the STFT has the limitations (a) the window size must be very small (b) It does not give multi-resolution information. So, to overcome this problem, wavelet transforms is used. Wavelet transform is shifted and scaled version of the mother wavelet. The continuous wavelet transforms and mother wavelet of $f(x)$signal may be expressed by eq. (1)

$$W_s f(x) = \ f(x)\Psi(x) = \frac{1}{s} \tag{1}$$

Where‘s’ is a scaling factor and Ψ_s (x) $=\frac{1}{s}\ \Psi\left(\frac{x}{s}\right)$ is pre-dilation of basic wavelet (x) with scaling factor ‘s’.

For s = 2^j, the wavelet transform is known as DWT (digital wavelet transform). The wavelet transform of a digital Signal $f(n)$is calculated by mallet algorithm as given in eq. (2) and (3)

$$s_2^j\ f(n) = \sum h_k\, s_2^{j-1} f\left(n - 2^{j-1}k\right) \tag{2}$$

$$W_2^j f(n) = \sum g_k\, W_2^{j-1} f\left(n - 2^{j-1}k\right) \tag{3}$$

Where s_2^j is a Smoothing operator and$s_2^0\ f(n) = d(n)$, where $d(n)$is digital signal to be and $W_2^j f(n)$ is the wavelet transform of the digital Signal$f(n)$. $\sum h_k$ and $\sum g_k$ are the coefficients of a low pass filter $H(w)$ and high pass filter $G(w)$ respectively.The DWT (discrete wavelet transforms) is achieved from the continuous wavelet transform by using sampling. In DWT, the ECG signal is decomposed into two components, one is low frequency component and other is high frequency component. For the analysis of high frequency signal a narrow window known as detail co-efficient is used. On the other hand, wider window known as approximation co-efficient is used for the analysis of the low frequency signal (Martis and Acharya , 2013).

In this paper, we proposed a method based on wavelet transform (db4) is used to decomposed the electrocardiogram (ECG) signal up to tenth level into detail co-efficient (Cd1, Cd2, …, Cd10) and approximate co-efficient (Ca1, Ca2, …, Ca10). The plots of decomposition of electrocardiogram signal (ECG) signal are shown in figure 6 and figure 7. The co-efficient Ca9 and Ca10 contain low frequency components having range similar to baseline wander and Cd1, Cd2 contain high frequency components. So, by using wavelet the co-efficient Ca9, Ca10 and Cd1, Cd2 are discarded. Remaining co-efficient keep as it is because these co-efficient contain the important information. In this proposed work, there are different databases analyzed with different record i.e. MIT-BIH databases are 100, 101, 102, 103, 104, 105, 106 and European ST-T database are e0103, e0104, e0105, e0106, e0107, e0108 and Long-Term ST databases are S20011, S20021, S20031, S20041, S20051, S20061, S20071.

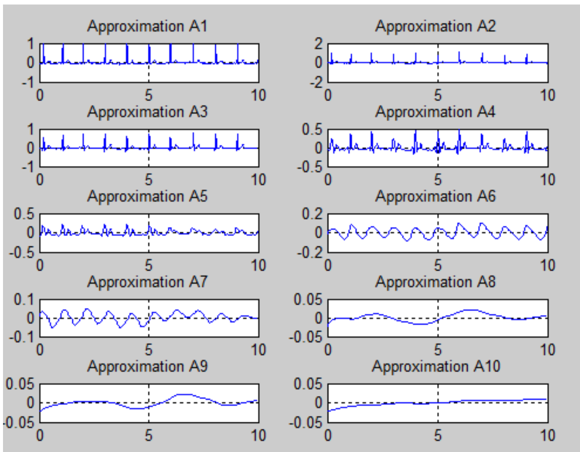


Figure6. Decomposition of ECG signal into approximate co-efficient using wavelet transforms

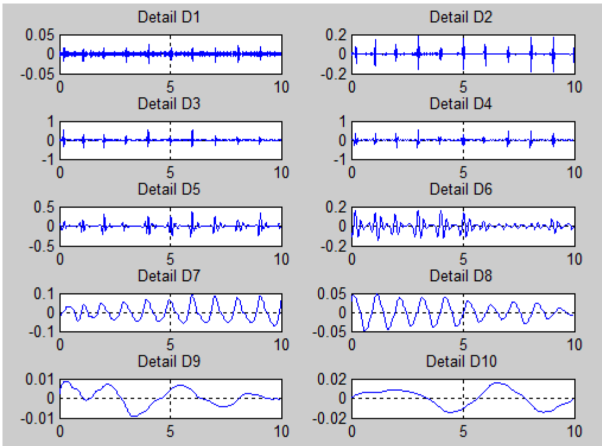
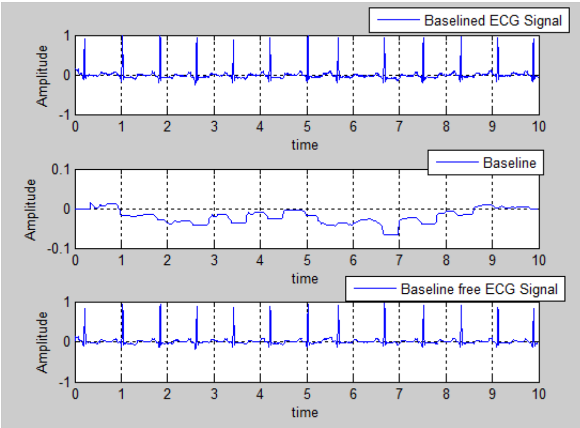


Figure7. Decomposition of ECG signal in detailed co-efficient using wavelet transforms

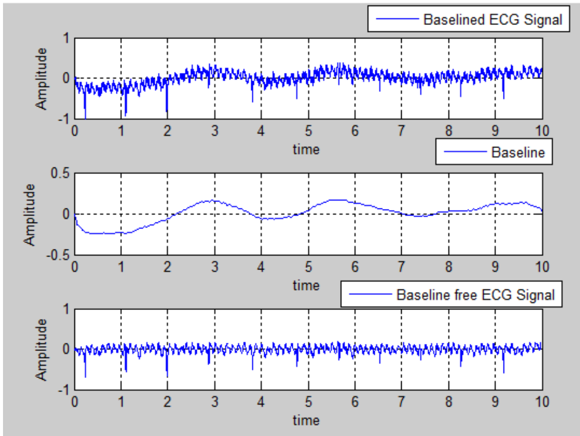
Results& Discussion

Removal of Baseline Wander

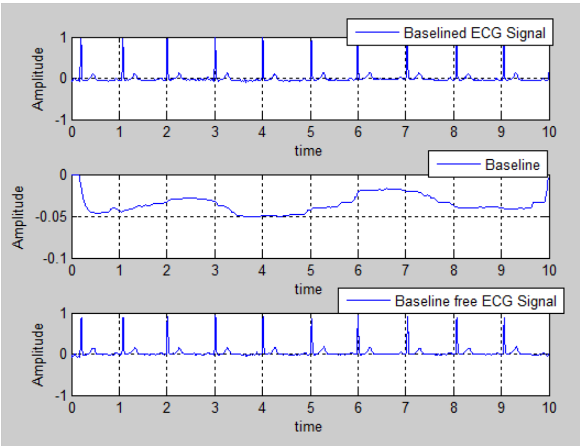
When baseline wander noise occurs in the ECG signal then the signal gets diverted from zero base line instead of being straight. This noise is also caused by the placement of improper electrodes, movement of patient and breathing. The adverse effect of this artifact in the electrocardiogram (ECG) signal leads to difficulties in the detection of the electrocardiogram (ECG) signal.



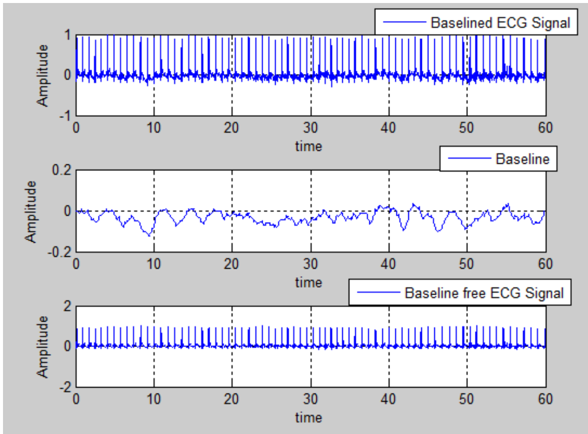
(a)100 record



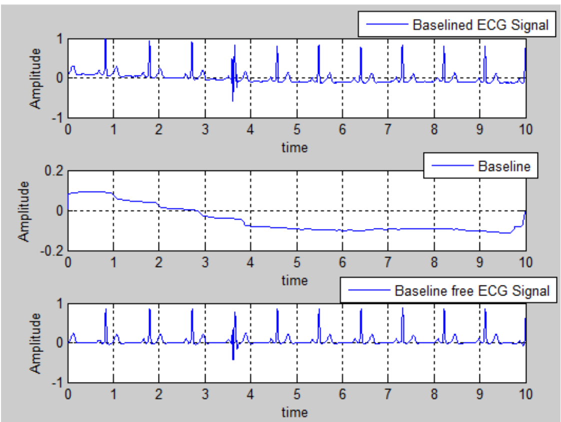
(b)101 record



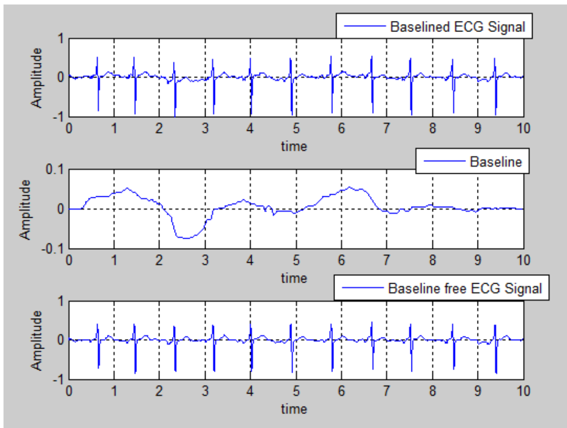
(c)e0103 record



(d)e0104 record



(e)S20011 record



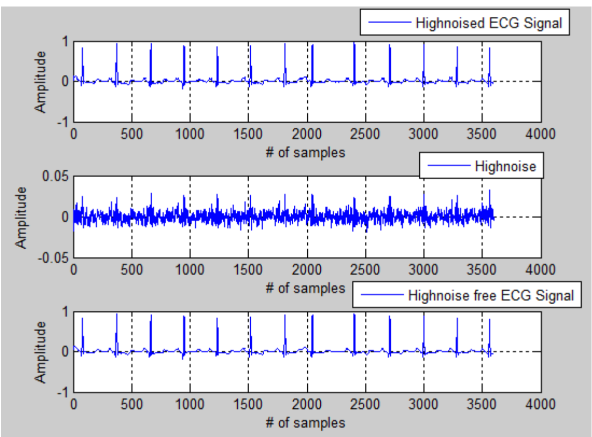
(f)S20021 record

Figure8. Results showing removal of baseline wander for different records of different database a) 100 b) 101 c) e0103 d) e0104 e) S20011 f) S20021

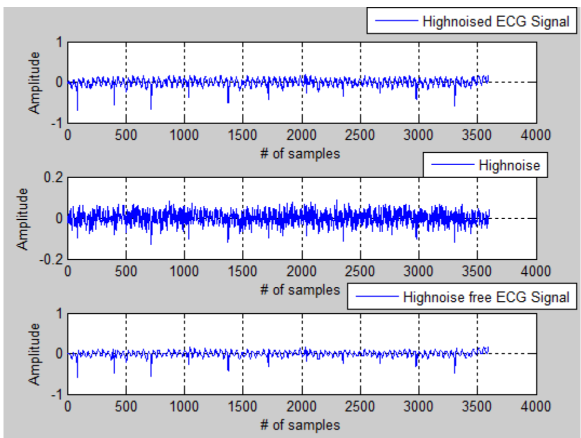
The range of frequency of this artifact is 0.5 to1 Hz. In this proposed work, the electrocardiogram (ECG) signal is decomposed up to tenth level into approximation co-efficient and detail co-efficient (Manocha and Singh, 2016). So, the last approximate co-efficient A9 and A10 are discarded to zero which contain frequency of baseline wander. The results showing removal of baseline wander for records of different database (100, 101, e0103, e0104, S20011, S20021) are shown in figure 8. These figures show that baseline ECG signal, detected baseline and baseline free ECG signal.

Removal of High Frequency Noise

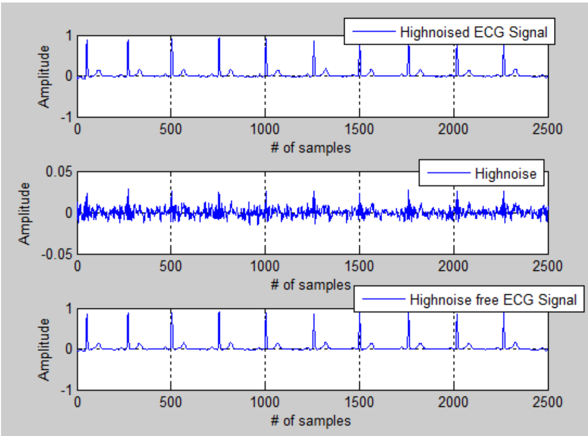
During Recording, high frequency noise overlaps the characteristics of the electrocardiogram (ECG) signal that makes the analysis of electrocardiogram (ECG) signal very difficult for the highly skilled doctors. The frequency range of high noise is 100Hz to150 Hz. This kind of noise cannot be efficiently reduced by using a proper band pass filter. So, wavelet transform function is used for removal of High frequency noise. The removal of baseline signal is shown in figure 8(a), 8(b), 8(c), 8(d), 8(e), 8(f) is a low frequency noise that shifts up and down the DC level. For the elimination of low frequency noise, initially take the median of ECG signal using one-stage median filter and subtracted from the applied input signal and then the output of median filter is passed to Savitzky-Golay filter for smoothing the waveform and we got baseline free ECG signal. After that wavelet transform (db4) is used to decomposed ECG signal up to tenth level into detail co-efficient (Cd1, Cd2, …, Cd10) and approximate co-efficient (Ca1, Ca2, …, Ca10) So, by using wavelet, the co-efficient Cd1, Cd2 are discarded which comprises of high frequency noise. The results for removal of high frequency noise for records of different database (100, 101, e0103, e0104, S20011, S20021) are shown in figure 9(a), 9(b), 9(c), 9(d), 9(e), 9(f). These figures show that high noised ECG signal, detected high noise and high noise free ECG signal.



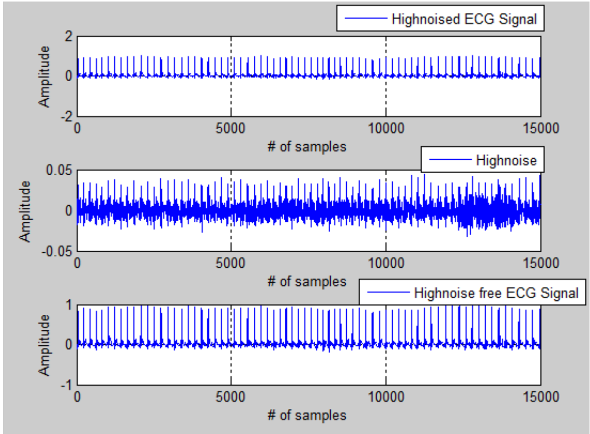
(a)100 record



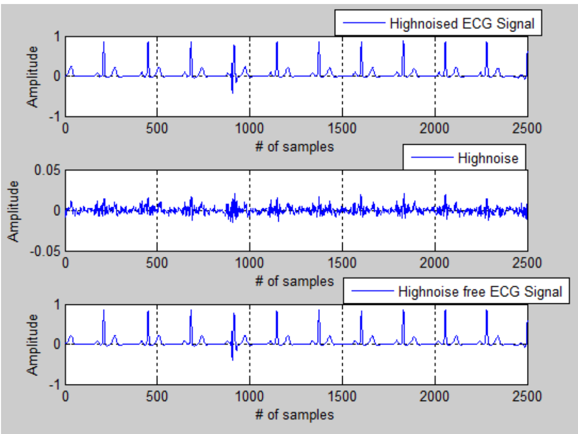
(b)101 record



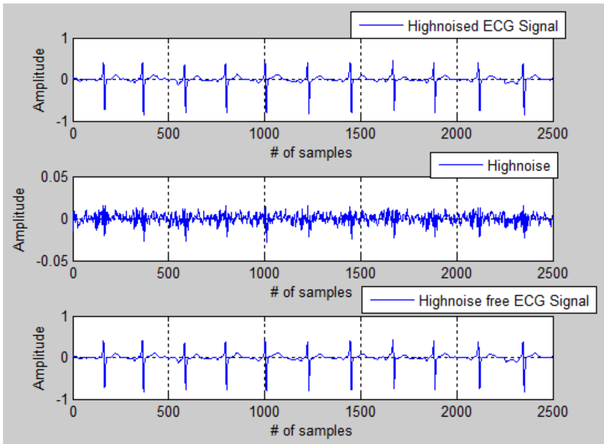
(c)e0103 record



(d)e0104 record



(e)S20011 record



(f)S20021 record

Figure9. Results showing removal of baseline wander for different records of different database a)100 b) 101 c) e0103 d) e0104 e) S20011 f) S20021

Comparison with Existing methods

For the elimination of high frequency noise and baseline wander, various techniques are analyzed and have been explained in introduction part. In (Sangaiah et al., 2019) wavelet transform method is used for MIT-BIH database comprises with IIR filter for the removal of noises and SNR (Signal to noise ratio) is calculated. In (Manocha and Singh, 2015) a method based on wavelet transform is employed for European database for the removal of noises and PRD is calculated after usage of different families of wavelet. In this proposed work, the comparison between SNR and MSE is done with different databases using (Sangaiah et al., 2019; Zhang and Wang, 2019). Here the Signal to Noise ratio, MSE for these databases are calculated and provide better results as shown in Table1, Table2

Table1. Comparison of the Signal to Noise Ratio using different records of different database

Sr.No	Record of different database			SNR(dB)			
	European ST-T database	Long-Term ST database	MIT-BIH Database	Wavelet transform with IIR filter for MIT-BIH database (Sangaiah et al., 2019)	Wavelet transform +Median filter+SG filter median filter for European ST-T database (Proposed)	Wavelet transform +Median filter+SG filter median filter for Long-Term ST database (Proposed)	Wavelet transform +median filter+SG filter Median filter for MIT-BIH Database (Proposed)
1	e0103	S011	100	-9.6034	27	30.91	26.13
2	e0104	S021	101	-4.2652	25	26.906	8.589
3	e0105	S031	102	-7.5858	30	25.33	27.01
4	e0106	S041	103	-4.2652	24.85	30.8677	29.68
5	e0107	S051	104	-4.6572	21.898	18.04	28.53
6	e0108	S061	105	-5.2787	27	23.1814	29.53
7	e0110	S071	106	-6.75	22.2746	24.49	25.89

Table 2. Comparison of the Mean square error using different records of different database

Sr.No	Record of different database			SNR(dB)			
	European ST-T database	Long-Term ST database	MIT-BIHDatabase	Wavelet transform with sub-band smoothing filter for MIT-BIH database (Zhang and Wang, 2019)	Wavelet transform +median filter+SG filter median filter for European ST-T database (Proposed)	Wavelet transform +median filter+SG filter median filter for Long- erm ST database (Proposed)	Wavelet transform +median filter+SG filter median filter for MIT-BIH Database (Proposed)
1	e0103	S20011	100	0.00015	4.7387 e-06	2.7919 e-06	8.9094 e-06
2	e0104	S20021	101	0.00018	6.0501 e-05	5.0086 e-06	1.9905 e-06
3	e0105	S20031	102	0.00014	2.6055 e-06	8.4463e-06	1.041 e-06
4	e0106	S20041	103	0.00019	1.3532 e-05	2.6328 e-06	5.1858 e-06
5	e0107	S20051	104	0.00018	1.5417 e-05	1.6885 e-04	7.6531 e-06

Conclusion

In this paper, different techniques have been used i.e. median filter is used for removal of DC component, Savitzky-Golay filter(SG) for smoothening of noise waveform and to remove various artifacts, decomposition of ECG signal is done by using wavelet transform. Wavelet transform provides the information in frequency and time domain whereas the thresholding has been used for the implementation of algorithms in MATLAB. The measured results i.e. MSE and SNR have been calculated using different record of different databases like European ST-T database, MIT-BIH, Long-term ST database. Moreover, the results of proposed work are compared with the existing works and found these results of proposed work are better than the existing work.

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