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Performance Comparison of Various Conventional Electrocardiogram De Noising Techniques

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ABSTRACT

Background: Electrocardiogram (ECG) is the interpretation of the electrical activities of the heart and plays a vital role in the diagnosis and monitoring of the health of heart. Recorded electrocardiogram signals are corrupted by noises like baseline wander, power line interference and artifacts. Suitable filters have to be designed to suppress the noises present in electrocardiogram signal and to obtain the original information. The performance of the filter will be evaluated based on the Signal to Noise Ratio (SNR) value. **Objective:** To remove the baseline and power line noise present in the recorded electrocardiogram signal. **Results:** The signals considered here are taken from MIT-BIH Arrhythmia database. The methodology of filtering an electrocardiogram signal using a combination of high pass filter along with wavelet and Kalman filter yields an improved signal to noise by removing the power line and baseline noises in the recorded signal. **Conclusion:** By combining the conventional techniques of Wavelet and Kalman filter, there is a considerable increase in signal to noise ratio after denoising of the electrocardiogram.

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INTRODUCTION

Computer aided signal analysis is a popular trend nowadays. For accurate signal analysis, the noises present in the electrocardiogram have to identified and removed. The noises present are power line interference with a frequency of 50 Hz, baseline wander noise, electromyographic (EMG) interference, motion artifacts and noise due to lose contact of electrodes. Therefore, it is necessary to remove these noises present in the electrocardiogram in order to infer the exact information from the signal. In this paper conventional methods such as high pass filtering, wavelet is filtering and Kalman filtering are combined together to de-noise the signal and the performance is evaluated based on the SNR value obtained.

MATERIALS AND METHODS

A.MIT-BIH Arrhythmia Database:

MIT-BIH arrhythmia database consists of 48-half-hour ECG recordings. The recordings were digitized at 360 Hz (samples per second per channel) with 11-bit resolution over 10 mV. ECG recordings are of two channels. The upper signal is modified by placing the electrodes on the chest and the lower signal is usually a modified one and recorded by placing the electrodes on the chest. Normal QRS complexes are usually prominent in the upper signal.

B. Noises in electrocardiogram:

Electrocardiogram (ECG) is the interpretation of the electrical activities of the heart. Recorded electrocardiogram signals are corrupted by noises like baseline wander, power line noise and artefacts.

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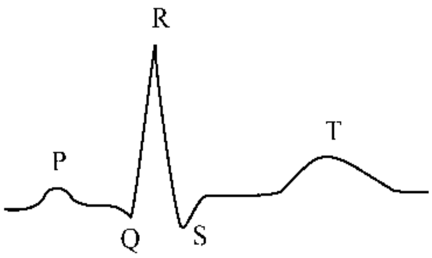

Fig. 1: Electrocardiogram wave

The above Figure 1 represents the normal electrocardiogram composed of a PQRST wave.

Amplitude:
P-wave : 0.25 mV
R-wave : 1.60 mV
Q-wave : 25% R wave
T-wave : 0.1 to 0.5 mV

Duration:

R-R interval	: 0.12 to 0.20 s
Q-T interval	: 0.35 to 0.44 s
S-T interval	: 0.05 to 0.15 s
P-wave interval	: 0.11 s
QRS interval	: 0.09 s

Power line interference:
Power line interference is the major noise present while recording the electrocardiogram (ECG) signal. The interference is caused due to the power lines that carry the recorded ECG signal from patient and it has the frequency of 50 Hz. This noise degrades the signal quality and makes it difficult for the doctors to analyse the signal.

Baseline Wander:
Baseline Wander is a low frequency (<0.03 Hz) noise produced by respiration of the patients or the instruments that results in a baseline drift of the electrocardiogram signal. Baseline is the zero flow line and the added noise causes the baseline to drift from its position, thus produces inaccuracies in the measured signal.

Motion Artifact:
Motion artefact is either due to loose contact of electrode or due to the continuous change in the physical position of the patient. It causes the baseline to drift from its actual position.

Electromyographic interference:
Electromyographic interference is due to the electrical activity of muscles. Electrodes are placed on the skin and used to test for muscle disorder. Its amplitude is about 10% of electrocardiogram.

C. Implementation of filter:
Digital filter plays an important role in digital signal processing. Digital filter produce more accurate result with less error when compared to analog filters. The Butterworth filters are signal processing filters that have flat frequency response. It is also referred to as a maximally flat magnitude filter. An ideal filter should have uniform sensitivity for the wanted frequencies.

A high-pass filter (HPF) is an electronic filter that passes high frequency signals but attenuates signals with frequencies lower than the cutoff frequency. Butterworth filter is said to have a property of maximally flat frequency response and no ripples in the pass band. It rolls off towards zero in the stop band.

Wavelet Denoising:
Wavelet transform gives both time and frequency domain information and is performed by a pair of filters namely low pass filter and high pass filter as proposed in Brij N.Singh [2006],Arvinti[2010]. The Fast Fourier Transform (FFT) loses the information in time domain and gives only spectral information in the frequency domain. To overcome this, Short Time Fourier Transform (STFT) was proposed and it represents the signal in both time and frequency domains using moving window function.

The window size is constant in order to reject the multi resolution information on the signal. Wavelet transforms holds the property of multi resolution to give both time and frequency domain information in a simultaneous manner through variable window size.

Continuous Wavelet Transform (CWT):

The continuous wavelet transform of the signal $x\,(t)$ is defined as a convolution of a the signal with a scaled and translated version of a base wavelet function,

$$W_a x(b) = \int_{-\infty}^{+\infty} x(t) \cdot \Psi_{a,b}(t) dt = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t) \cdot \Psi\left(\frac{t-b}{a}\right) dt \qquad \text{Eq. 1}$$

where the scale 'a' and translation 'b' parameters are nonzero real values and the wavelet function is real and $\Psi_{a,b}(t)$ denotes the mother wavelet function in equation. 1. If 'a' is small then it gives a contracted version of the mother wavelet function and high frequency components are analyzed. For large value of 'a' the basic function is stretched and provides the analysis of low-frequency components of the signal.

Discrete Wavelet Transform (DWT):

The discrete wavelet transform is defined as a convolution between the analyzed signal and discrete dilation and translation of a discrete wavelet function. In its most common form, the DWT applies a dyadic grid (integer power of 2 scaling with 's'and 'l') and orthonormal wavelet basis function:

$$\Psi_{(s.l)}(x) = 2^{\frac{-s}{2}} \Psi(2^{-s}x - l) \qquad \text{Eq. 2}$$

The variables s and l are integers that scale and translate the mother function $\Psi$to generate wavelets in equation. 2. The s indicates the wavelet's width, and l gives its position.

Wavelet filters:

In wavelet transform filtering of the input signal as dealt by Chouakri etal [2005] and Karthikeyan etal [2011]. SA is done by a pair of filters such as low pass filter (LPF) and high pass filter (HPF) and the cut off frequency is the middle frequency of input signal. Approximation Coefficient (CA) corresponds to low pass filter and the Detailed Coefficient (CD) corresponds to high pass filter. While filtering the CA is divided into new approximation and detailed coefficients. This decomposition is carried out until the required frequency response is achieved.

Wavelet thresholding:

Wavelet thresholding is the signal estimation technique that exploits the capabilities of signal denoising. Thresholding method is categorized into two types such as hard thresholding and soft thresholding. Wavelet thresholding leads setting of small wavelet coefficient to zero and retaining or shrinking the coefficients corresponding to desired signal.

It is reasonable to assume that small coefficients are due to noise and can be set to zero. Certain pre-processing steps are necessary to denoise the electrocardiogram signal.

Steps in wavelet denoising:

- Decompose the input signal using discrete wavelet transform.
- Choose a wavelet and determine the decomposition level.
- Select the thresholding method.
- Apply the thresholding on each level of wavelet decomposition. The coefficients above the threshold value will be removed.

The resultant denoised signal is obtained without affecting any features of signal. In the above steps, the most critical is to select the proper threshold. Because, it directly reflects the quality of the de-noising.

Using the threshold selection rules, the threshold value has been calculated in each decomposition level and the coefficients above the value of threshold have been removed. In electrocardiogram signal there will not be any useful information above 100Hz and those coefficients are changed into zero.

Usually the baseline wander lies in the frequency range of less than 1 Hz. The coefficients corresponding to that range also removed. The denoised electrocardiogram will be obtained as a result of applying threshold on each level of the original signal.

Here Daubechies4 wavelet is used. Daubechies wavelet is used because of its efficient denoising and its compact support. It reduces the computation time and analyzes the signal at different frequencies.

Kalman filter review:

The Kalman Filter (KF) is a powerful tool in the analysis of a dynamical model in time. The filter is used to obtain recursive estimation of the parameters. The model can be written in a state – space form and the employment of Kalman filter provides with an estimation of the Auto Regressive (AR) parameters which can be used for the estimation of the non – stationary signal. It is also demonstrated the usage of parameters as input features of the signal in a clustering approach.

The Kalman filter is an estimator with properties like optimality in the Minimum Mean Square Error (MMSE).The estimators used to overcome smoothing are fixed-lag, fixed-point and fixed interval.

The difference between the two estimators, the Kalman filter and the Kalman smoother, it is related based on usage of observations to perform estimation. The Kalman filter uses only the past and the present observations to perform estimation, while the Kalman smoother uses also the future observations for the estimation. Both estimators are recursive in nature.

This means that the estimate of the present state is updated using the previous state only and not the entire past states. The state of the model can be known by analyzing the observations. The Kalman filter is also a computational tool and problems may exist due to the finite precision arithmetic of the computers.

The Kalman filter and the Kalman smoother have been extensively used in biomedical signal processing by Povinelli. RJ. etal [2006], Omid Sayadi [2008] and Poornachandra.S.etal[2008]. The model for the observations must be written in a state – space form, so that the Kalman filter or the Kalman smoother can be applied.

A state space model is represented by two equations. First equation describes the evolution of the parameters and the second equation describes the relation of the parameters with the observations:

$$x_t = Ax_{t-1} + w_t \qquad \text{Eq. 3}$$

$$y_t = Cx_t + v_t \qquad \text{Eq. 4}$$

The two equations 3 and 4 represent a state space model where $x_t$denotes the parameters in time *t*, $y_t$denotes the observations, $w_t$denotes the state noise with zero mean and covariance matrix *Cw*, $v_t$is the observation noise with zero mean and covariance matrix *Cv*, *A* is the state transition matrix and *C* is the observation matrix. The matrices *A* and *C* and the covariance matrices *Cv* and *Cw* are assumed to be known.

A non-linear model for the electrocardiogram signal is used. It uses the model for electrocardiogram de-noising and compression. Kalman filter is used to detect and to extract periodic noise from the electrocardiogram. The coefficients are assumed to change with time.

A classical problem in estimation theory is the estimation of the hidden states, which are observable through a set of measurements. The conventional Kalman filter assumes a linear model for the system dynamics and observation equations. In order to extend the idea of the conventional Kalman filter to such systems, several variants of the original Kalman filter have been developed.

The electrocardiogram signal is given as input to Kalman filter and after de-noising by updating the values recursively, the signal to noise ratio is calculated and compared with other de-noising techniques. The de-noised output is compared with other de-noised outputs and the method with best signal to noise ratio is used further.

Signal to Noise Ratio (SNR):

In signal processing, noise is a general term used to refer unwanted signal. Sometimes the word is also used to mean signals that are random (unpredictable) and carry no useful information. SNR is expressed in decibels (dB).

Noise reduction, the recovery of the original signal from the noise-corrupted signal, is a very common goal in the design of signal processing systems, especially filters. It is the ratio of the original signal to noise removed from the signal. Signal to noise ratio for different electrocardiogram records are compared for different filters. Signal to noise compared for different filters. Signal to noise ratio is expressed mathematically in equation. 5 as

$$SNR = 10 \log_{10} \frac{P_{signal}}{P_{noise}} (dB) \qquad \text{Eq. 5}$$

RESULTS AND DISCUSSION

The recorded electrocardiogram will have some noise like baseline wander, power line noise along with arrhythmias. Those noises are removed by applying the electrocardiogram signal to the corresponding filters. The recorded electrocardiogram signal is passed to the high pass filter. The obtained output has low frequency baseline wander is removed.

The output obtained from high pass filter is applied to Daubechies wavelet filter and the resultant signal in which power line interference is removed to some extent. The output obtained from wavelet filter is then applied to Kalman filter as a result the power line noise is removed further with improvement in signal to noise ratio. This procedure is done for various records and signal to noise ratio is compared.

For Record 101m:

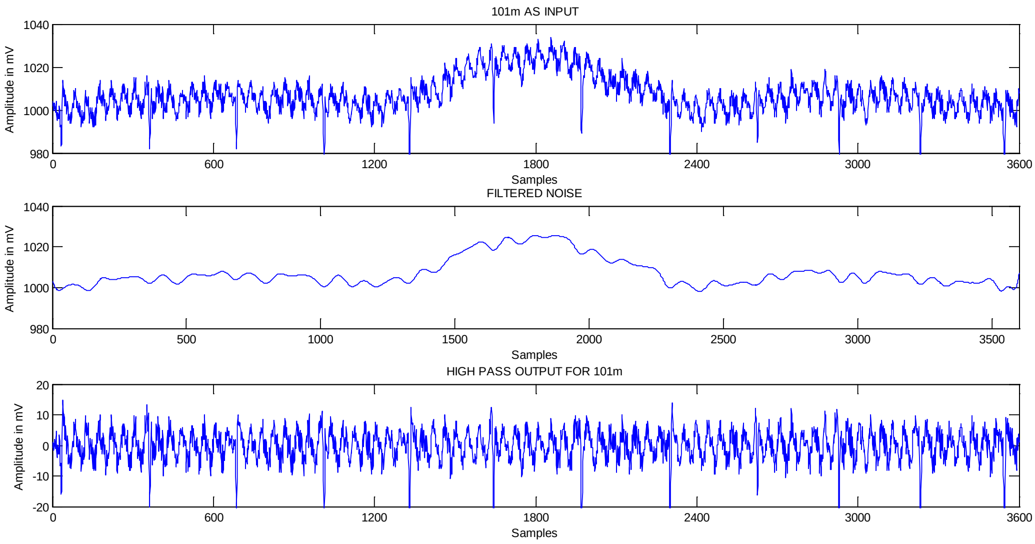

Fig. 2: High pass filter output for record 101m.

The Figure 2.shows the recorded electrocardiogram signal which is given to high pass filter to remove base line wander with cut off frequency of about 0.5 Hz for record 101m.

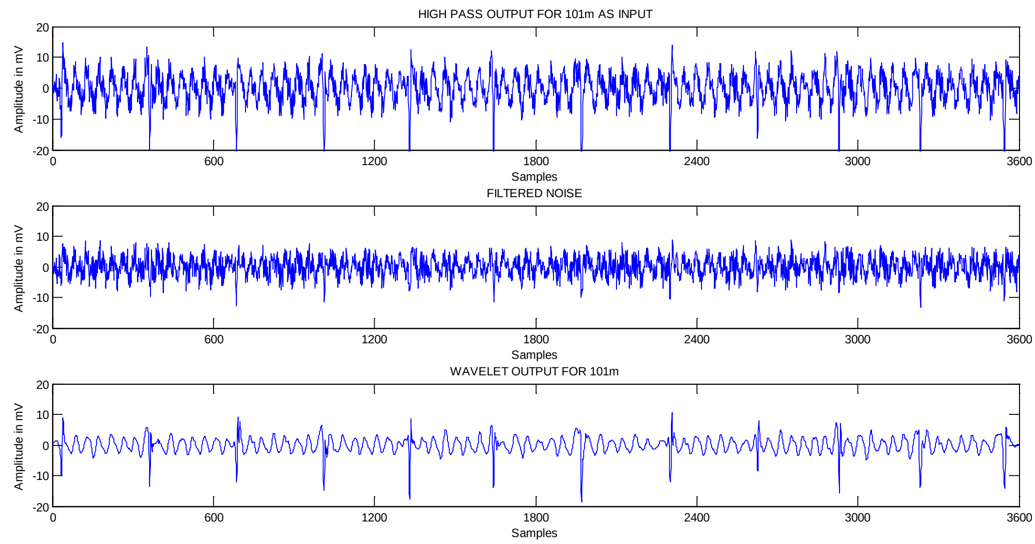

Fig. 3: Wavelet output for high pass output as input for 101m.

Figure 3.shows the wavelet output with high pass filter output as input. In this power line noise is removed for record 101m.

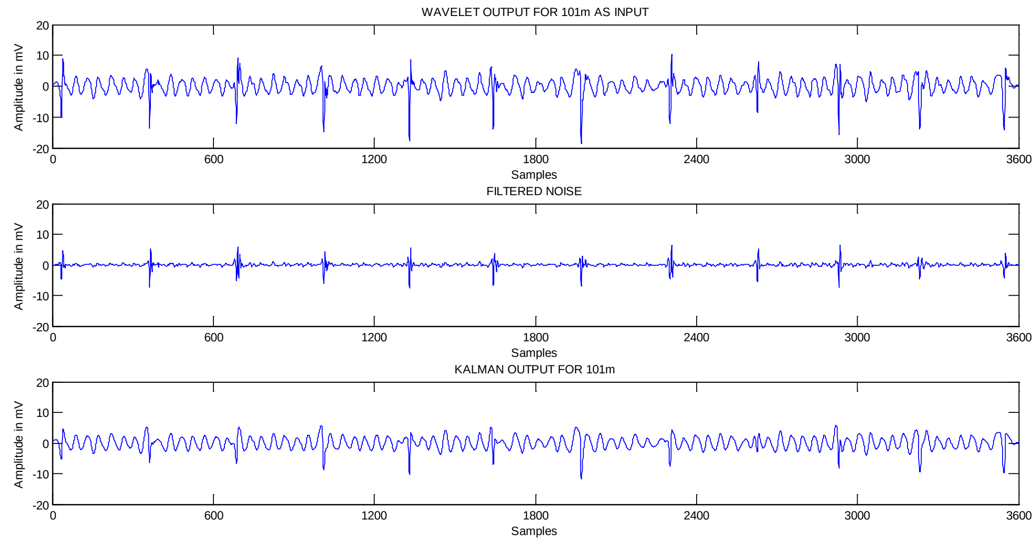

Fig. 4: Kalman output for wavelet output as input for 101m.

Figure 4.represents the Kalman filter output with wavelet output as input. In this filtering method power line noise is removed with improvement in signal to noise ratio for record 101m.

For Record 104m:

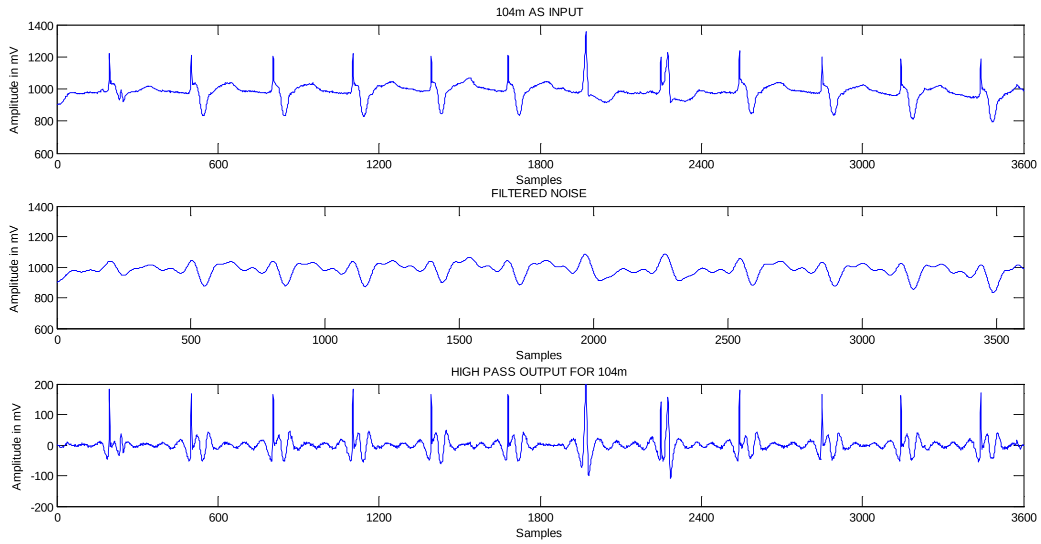

Fig. 5: High pass filter output for record 104m.

The Figure 5 shows the recorded electrocardiogram signal which is given to high pass filter to remove base line wander with cut off frequency of about 0.5 Hz for record 104m.

Australian Journal of Basic and Applied Sciences, 8(2) February 2014, Pages: 132-144

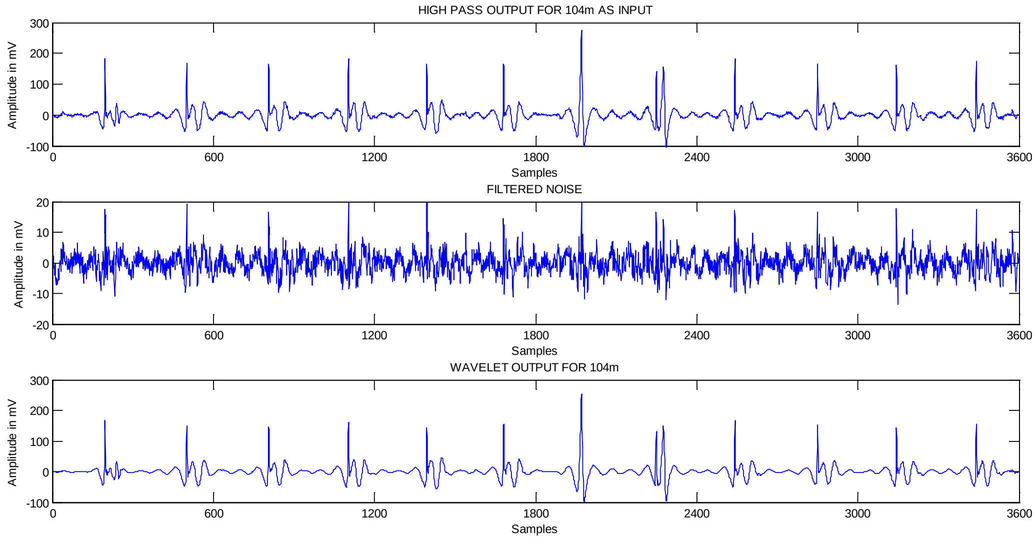

Fig. 6: Wavelet output for high pass output as input for 104m.

Figure 6.shows the wavelet output with high pass filter output as input. In this power line noise is removed for record 104m.

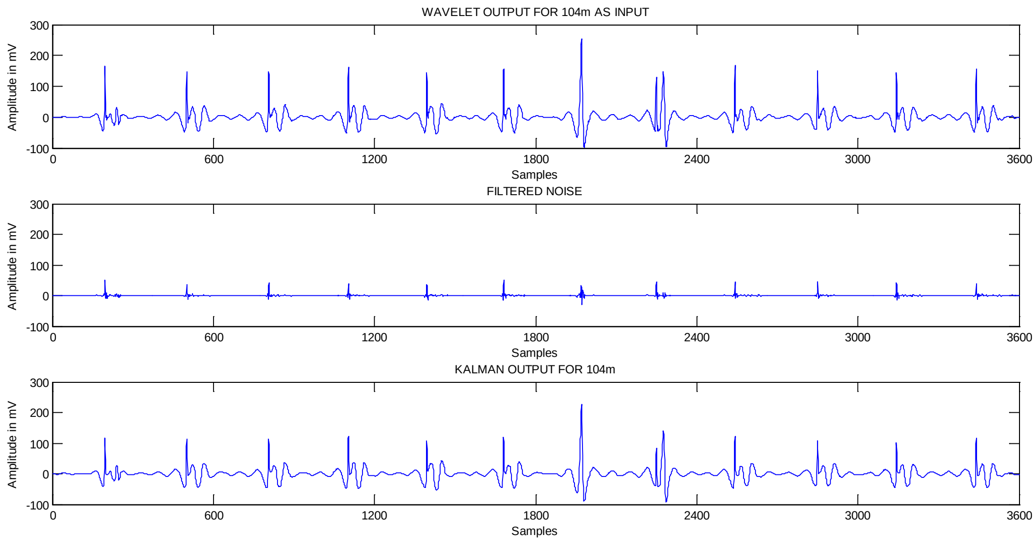

Fig. 7: Kalman output for wavelet output as input for 104m.

Figure 7 represents the Kalman filter output with wavelet output as input. In this filtering method power line noise is removed with improvement in signal to noise ratio for record 104m.

For Record 105m:

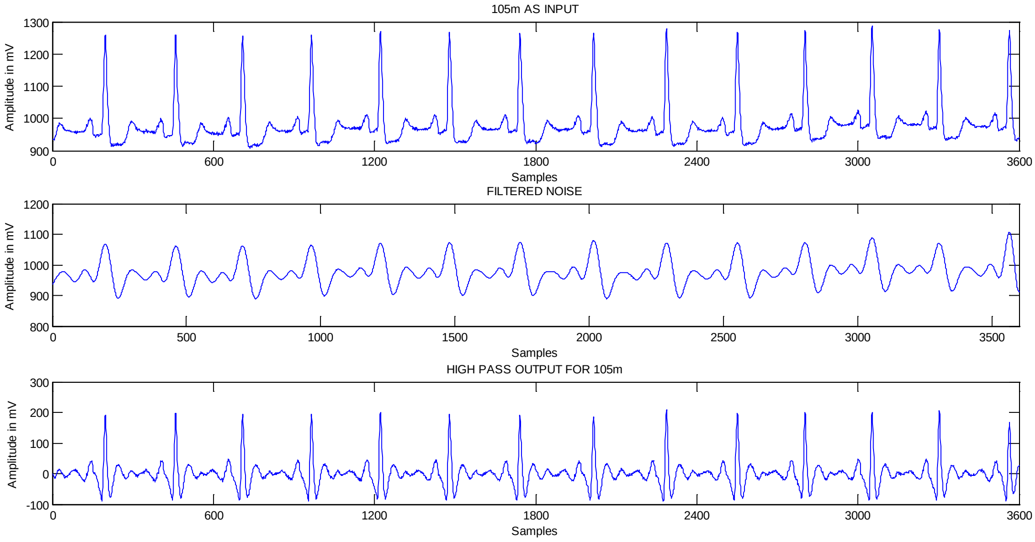

Fig. 8: High pass filter output for record 105m.

Figure 8 shows the recorded electrocardiogram signal which is given to high pass filter to remove base line wander with cut off frequency of about 0.5 Hz for record 105m.

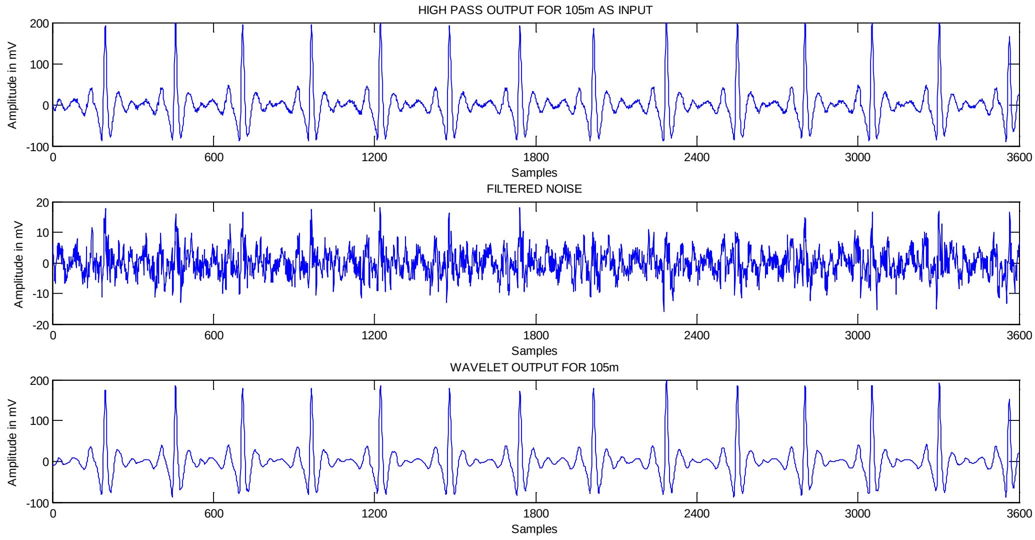

Fig. 9: Wavelet output for high pass output as input for 105m.

Figure 9.shows the wavelet output with high pass filter output as input. In this power line noise is removed for record 105m.

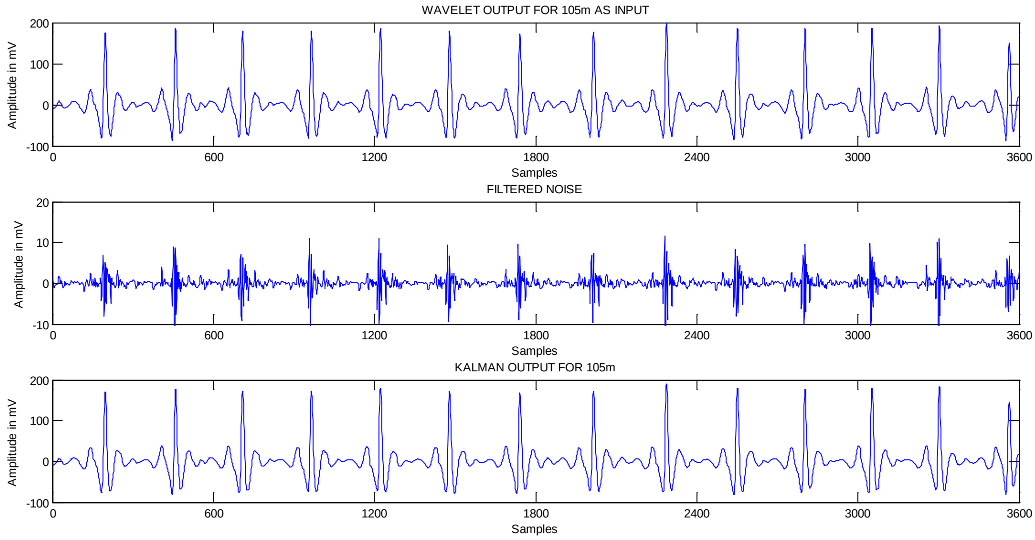

Fig. 10: Kalman output for wavelet output as input for 105m.

Figure 10.represents the Kalman filter output with wavelet output as input. In this filtering method power line noise is removed with improvement in signal to noise ratio for record 105m.

For Record 121m:

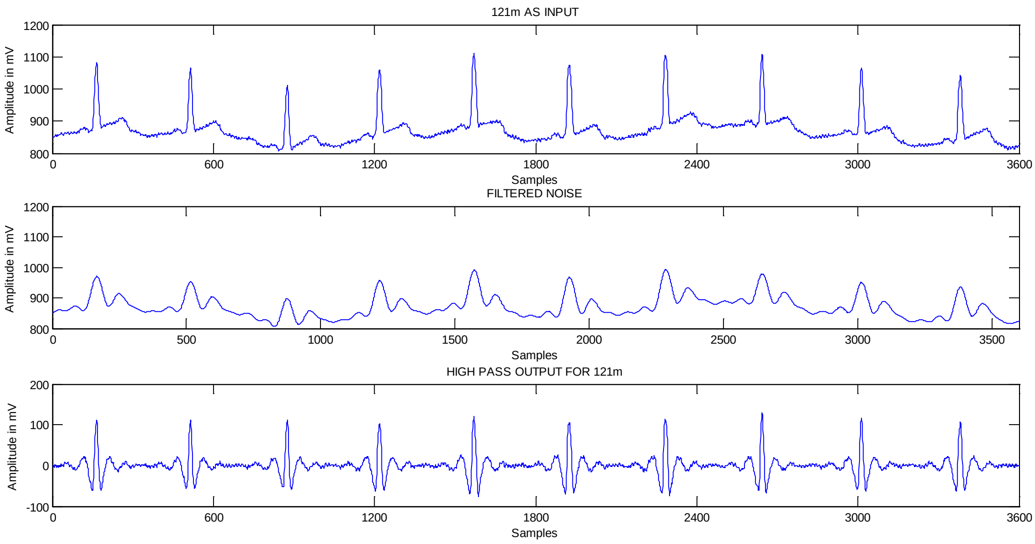

Fig. 11: High pass filter output for record 121m.

Figure 11 shows the recorded electrocardiogram signal which is given to high pass filter to remove base line wander with cut off frequency of about 0.5 Hz for record 121m.

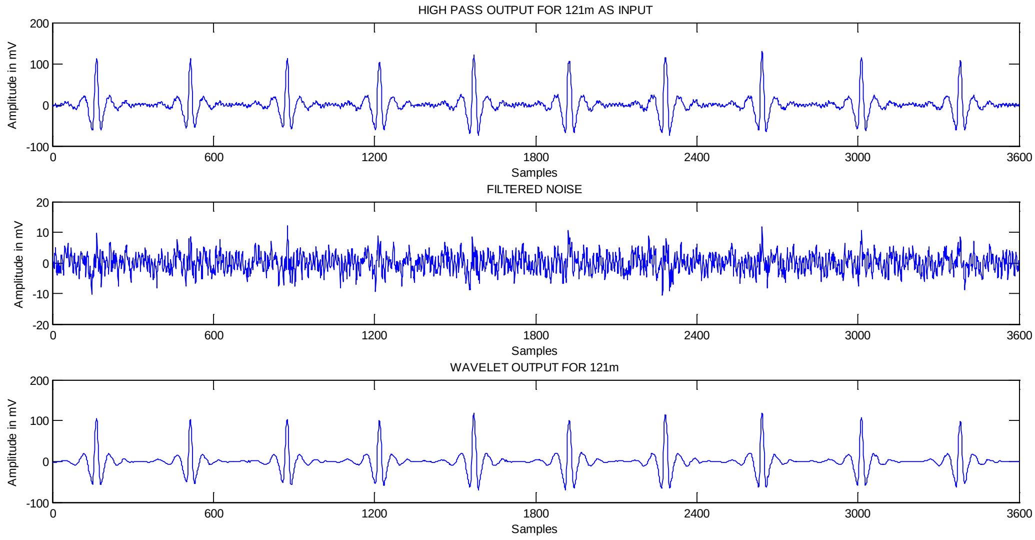

Fig. 12: Wavelet output for high pass output as input for 121m.

Figure 12.shows the wavelet output with high pass filter output as input. In this power line noise is removed for record 121m.

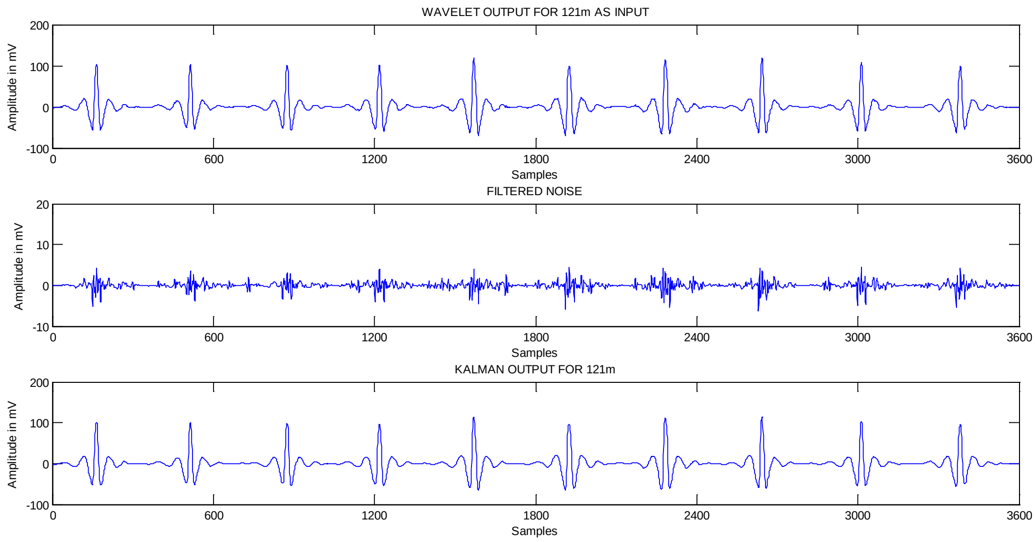

Fig. 13: Kalman output for wavelet output as input for 121m.

Figure 13.represents the Kalman filter output with wavelet output as input. In this filtering method power line noise is removed with improvement in signal to noise ratio for record 121m.

For Record 201m:

Australian Journal of Basic and Applied Sciences, 8(2) February 2014, Pages: 132-144

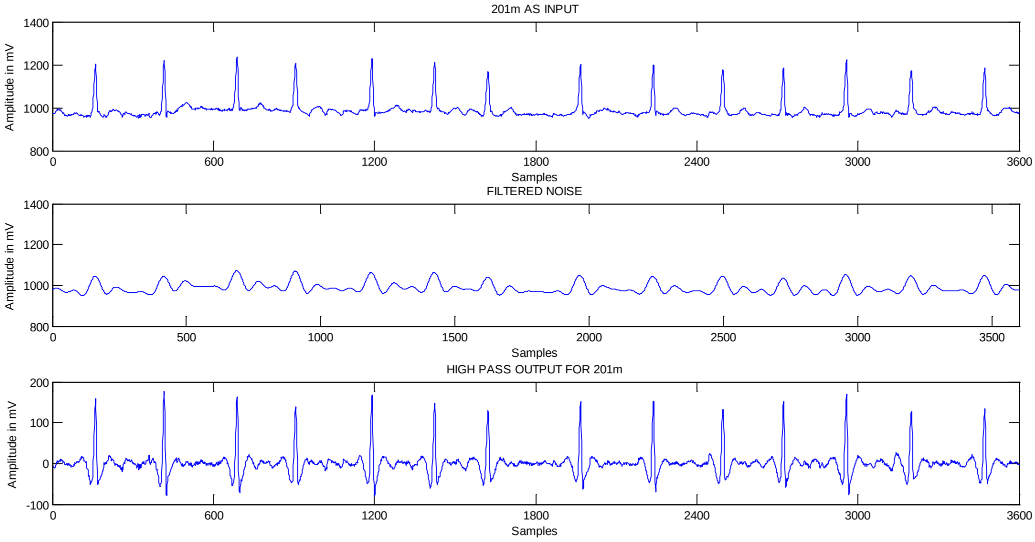

Fig. 14: High pass filter output for record 201m.

Figure 14 shows the recorded electrocardiogram signal which is given to high pass filter to remove base line wander with cut off frequency of about 0.5 Hz for record 201m.

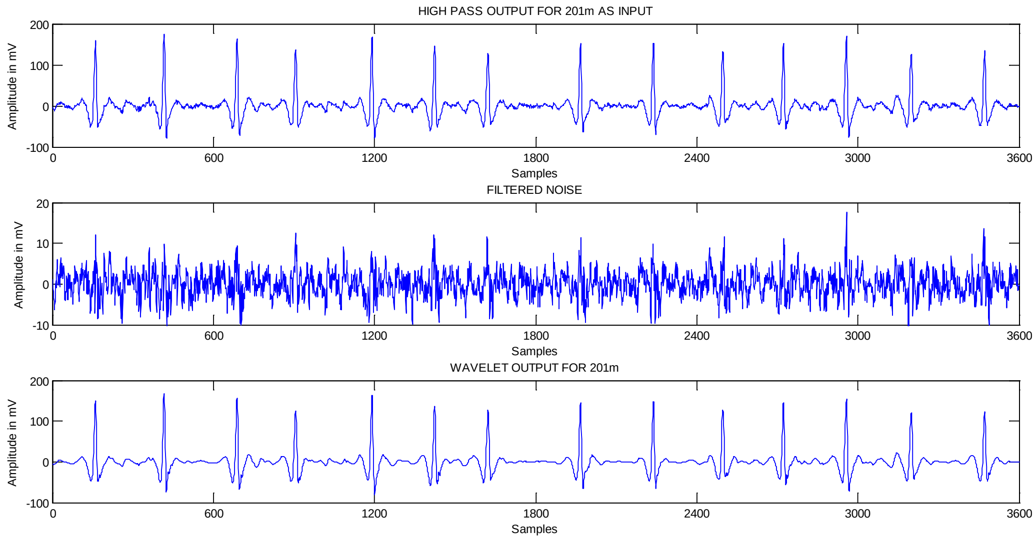

Fig. 15: Wavelet output for high pass output as input for 201m.

Figure 15.shows the wavelet output with high pass filter output as input. In this power line noise is removed for record 201m.

Australian Journal of Basic and Applied Sciences, 8(2) February 2014, Pages: 132-144

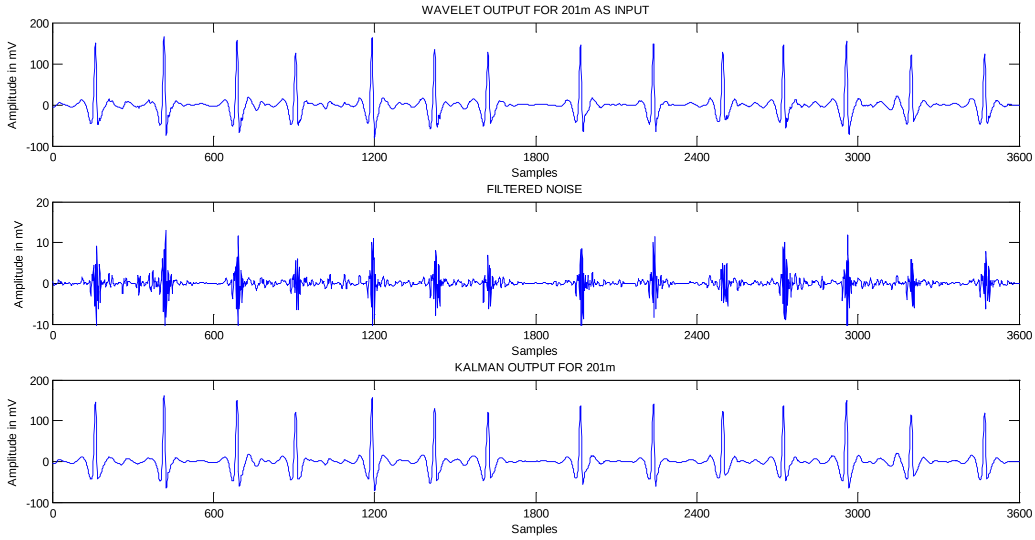

Fig. 16: Kalman output for wavelet output as input for 201m.

Figure 16 represents the Kalman filter output with wavelet output as input. In this filtering method power line noise is removed with improvement in signal to noise ratio for record 201m.

Table 1: SNR comparison for high pass, wavelet and Kalman filter.

SNR in dB for various ECG records					
Filter	Record 101m	Record 104m	Record 105m	Record 121m	Record 201m
HPF	1.8356	1.5146	3.2381	5.2416	2.9379
WAVELET	8.6197	23.2292	22.8800	23.7026	21.7682
KALMAN FILTER	20.4248	23.2855	30.5699	34.3992	27.8159

Table 1 shows the comparison of the signal to noise ratio obtained for various records. It indicates the signal to noise ratio improvement along with the removal of power line and baseline noise to a maximum extent using high pass, wavelet and Kalman filter.

Conclusion:

Artifacts and noises play a major role in ECG signal processing. It makes difficult for the doctors to diagnose the arrhythmia exactly. Hence, these noises should be analyzed and removed. The recorded electrocardiogram signal will be contaminated with noises like power line interference, baseline wander and with arrhythmias. It is difficult to extract the original information. So the noise corrupted electrocardiogram signal is first de-noised using high pass filter, as a result of which the baseline wander of low frequency is removed.

The output obtained from high pass filtering is given to Daubechies wavelet filter and power line noise is removed to some extent. The signal obtained from wavelet filtering is given to Kalman filter for better de-noising of power line noise with improvement in signal to noise ratio.

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