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De-noising the ECG Signal Using DWT and Kernel Adaptive Filter

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ABSTRACT: The use of electrocardiogram (ECG) plays significant role in the diagnosis of heart disease and human computer interface etc. But, the ECG signals get affected from different types of noise during data acquisition due to which it faces the problem to detect actual abnormality. De-noising of the ECG signal is so indispensable and for de-noising it various researcher work in this area. In this work, we propose an approach which uses DWT and together with kernel adaptive intensity transfer function extract the signal. The original ECG single is taken from MIT-BIH arrhythmia database is corrupted with dissimilar types of noise and is used for the analysis. The experimental analysis of the proposed approach is done in MATLAB using the performance measuring parameter such as MSE, PSNR and PRD. The simulation outcomes of the proposed gives improved results than the existing approach.

Keywords: ECG; De-noising, DWT, High Pass Filter, Kernel Function

I. INTRODUCTION

Now a days Electrocardiogram (ECG) technique is extensively used for measuring electrical activities of the heart. Analysis and processing of ECG signals are therefore important for detecting diseases of heart. But incorporation of noises transforms the amplitude and frequency of the ECG signals and as a consequence the detection of diseases would be difficult. Dissimilar de-noising methods have already been pioneered for extracting authentic information from noisy ECG signals. Among dissimilar methods performance of discrete wavelet transform (DWT) method is conspicuous. Lack of shift invariance and poor directional selectivity are the chief restrictions of DWT [1]. These restrictions can be circumvents by using complex wavelet transforms. Wavelet de-noising methods based on threshold algorithm was primary introduced by Donoho [2]. The threshold algorithm exploits the spatially adaptive multi-resolution feature of the wavelet transform. The benefits of this method comprise fast computation speed, extensive adaptability and best evaluation than any other linear estimates give. The most important confront of thresholding algorithm is to conclude an optimum threshold value. A small threshold value will not eliminate noise and the de-noised signal may still be raucous; whereas an outsized threshold value eliminates details from the decomposed data and the de-noised signal may be distorted [3]. The hard threshold function therefore fabricates visual distortion and the soft threshold function causes distorting of edges during signal modernization [4]. ECG is indispensable when a person faces problems such as breathing issues, heart attack, high blood pressure, high cholesterol etc. [5]. ECG gives the electrical commotion of the heart. Due to the abnormalities of the heart, the heart stops pumping of adequate blood to the brain and body and it consequences in dissimilar heart diseases. Frequency of an ECG signal varies from 0 Hz to 100Hz and the amplitude varies from 0.02 mV to5 mV. 50Hz power line interference is the foremost noise source in ECG [6] and it can be removed by filtering the signal with a 50Hz notch filter [7]. The other noises that counterfeit ECG signals are colored noise, white noise, electrode movement noise, muscle artifact noise, baseline shift and composite noise. ECG de-noising is therefore very essential as correct diagnosis of the signal does not take place because of these interferences.In this work, propose a DWT with high pass filter for de-noising the ECG signals. The original ECG taken from MIT-BIH arrhythmia database is corrupted with different types of noise and is used for the analysis. DWT and its expansive forms namely double density discrete wavelet transform, dual-tree discrete wavelet transform and double-density dual-tree discrete wavelet transform techniques employing thresholding algorithm are presented for ECG signal de-noising.

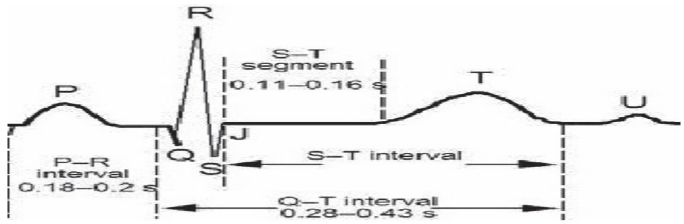

Fig. 1. ECG waveform for one cardiac cycle.

PRD, Peak Signal to noise ratio(PSNR) and root mean square error (RMSE) are the performance parameters used for the analysis. The algorithm developed on different approaches to ECG signal de-noising problem is simulated using MATLAB toolbox. The remaining section of the paper is organized as follows: Next section presents literature work for de-noising the ECG signal. In section III discuss about our proposed methodology. Section IV illustrated the experimental results and analysis and last section concluded the paper and also directs for future work.

II. RELATED WORK

Holambe and Patil [9] presented a new method of threshold estimation for ECG signal de-noising using wavelet decomposition. In this method, threshold is computed using the maximum and minimum wavelet coefficients at each level. Using this threshold and well known hard thresholding process, the significant wavelet coefficients from each level are selected and de-noised ECG signal is reconstructed with inverse wavelet transform. The performance of this method is compared with all well know wavelet shrinkage de-noising methods with bior4.4 wavelet using root mean square error (RMSE) and signal to noise ratio (SNR) on MIT-BIH ECG database. The proposed threshold estimation is simple and faster compared to all existing threshold calculation methods namely Visu Shrink, Sure Shrink, Bayes Shrink, and level dependent threshold estimation and gives better SNR and RMSE. Proposed threshold estimation process decreases data sorting and storing resources allowing low-cost and faster implementation for portable biomedical devices. Wang *et al.* [10] proposed a genetic optimized wavelet thresholding (GOWT) approach. A quadratic curve thresholding function (QCTF) was devised to realize the smooth connection of threshold points. Moreover, in terms of the root mean square error and the filtering smoothness, a new genetic algorithm was devised to automatically search the optimal parameters of QCFT for different noisy signals. Finally, the GOWT was evaluated and compared with hard thresholding and soft thresholding by means of MIT-BIH arrhythmia database ECG records. The filtering results indicate that the GOWT can realize smooth threshold transition, avoiding the oscillation at the cutoff threshold point caused by the hard thresholding and the wavelet coefficient bias brought by the soft thresholding. Its adaptability to various signals has been strengthened by the genetic algorithm. The GOWT can find a trade-off between the smoothness and distortion of signal filtering, generating the desirable noise-free signal for feature extraction. Huimin *et al.* [11] proposed a modified threshold de-noising method based on wavelet transform is adopted to improve the quality of a signal which has been polluted by noises. The method overcomes the discontinuous in hard threshold de-noising method and reduces the permanent bias in soft threshold de-noising method. At last soft threshold de-noising, hard threshold de-noising and modified threshold de-noising is used to reduce noises in the same signal by simulation. The results show that the modified threshold de-noising method is superior to the traditional soft and hard wavelet threshold de-noising methods in improving SNR and decreasing RMSE. Venkateswarlu and Raj [12] proposed the de-noising method which uses Undecimated Wavelet Transform to decompose the raw ECG signal and we performed the shrinkage operation to eliminate the noise from the noisy signal. In the shrinkage step we used semi-soft and stein thresholding operators along with traditional hard and soft thresholding operators and verified the suitability of different wavelet families for the de-noising of ECG signals. The results proved that the de-noised signal using UDWT (Undecimated Discrete Wavelet Transform) have a better balance between smoothness and accuracy than the DWT. Shemi and Shareena [13] presented a performance comparison of de-noising of ECG signals based on different wavelet transform techniques is implemented. Discrete wavelet transform (DWT) and its expansive forms such as double-density discrete wavelet transform (DDDWT), dualtree discrete wavelet transform (DTDWT) and double-density dual-tree discrete wavelet transform (DDDTDWT) techniques employing thresholding algorithm are presented for signal de-noising.

The ECG signals taken from MIT-BIH arrhythmia database are corrupted with different types of noise and used for the analysis. The results of MATLAB simulations show that the algorithm based on double-density dual-tree discrete wavelet transform is more effective and gives better performance in terms of both SNR and RMSE.

Mishra and Verma [14] presented the study of ECG signals using wavelet transform analysis. The Electrocardiogram (ECG) shows the electrical action of the heart and is used by physicians to check the heart's condition. Analysis of ECG becomes complex if noise is rooted with signal during acquirement. In this paper, de-noising techniques for ECG signals based on Decomposition will be compared. Firstly different wavelets will be applied like Haar, dbN and Symlet wavelet. Then thresholding technique will be applied for getting de-noised signal. Sawant and Patil [15] presented a wavelet de-noising method has been examined to eliminate noise from the ECG signal. Different thresholding algorithms are analyzed both theoretically and empirically. Ideal ECG signal and noise corrupted ECG signal are evaluated using MATLAB. Removal of noise because of muscle activity is difficult to handle because of the substantial spectral overlap between the ECG and muscle noise. Averaging techniques have been successfully applied to ECG signal for reduction of baseline wander noise. DWT has good ability to decompose the signal and wavelet thresholding is good in removing noise from decomposed signal. We applied wavelet transform on the input vector, thresholded it, inverse transformed it to finally achieve a signal with very low EMG noise. The analyses of thresholding techniques have been compared based on signal to noise ratio. It is observed that "rigrsure" method gives optimum performance.

III. PROPOSED METHODOLOGY

This section presents a methodology to confiscate the noise from the electrocardiogram signal. We use the discrete wavelet transform by applying kernel adaptive filtering technique which is linear adaptive filters in reproducing kernel Hilbert space. Wavelet de-noising methods deals with wavelet coefficients using a suitable chosen threshold value in advance. The wavelet coefficients at different scales could be obtained by taking DWT of the noisy signal. Normally, those wavelet coefficients with smaller magnitudes than the preset threshold are caused by the noise and are replaced by zero, and the others with larger magnitudes than the preset threshold are caused by original signal mainly and kept (hard-thresholding case) or shrunk (the soft thresholding case). Then the de-noised signal could be reconstructed from the resulting wavelet coefficients.These methods are simple and easy to be used in de-noising of ECG signal.

A. Discrete Wavelet Transform

The DWT of a signal "x" is calculated by passing it through a series of filters i.e. low pass and high pass filters [16, 17]. The inner product of the signal x(t) and the wavelet function ψ m, k provides a set of coefficients XDWT(m, k) for m and k by applying DWT on signal x(t). DWT can be considered as one of the multi-rate signal processing systems that use multiple sampling rates in the processing of discrete time signals. The DWT of a signal x(t) is given by :

$$X_{DWT_k} = \int_{-\infty}^{\infty} x t^{2^{m/2}} \psi(2^m t - k) dt$$

Where, ψ m, k is the wavelet function.

The discrete wavelet transform of a signal is calculated by passing it through a series of filters namely low pass filter and high pass filter. The coefficients associated with low pass filter is called approximation coefficients and high pass filtered coefficients are called detailed coefficients. This decomposition process is carried out until the required frequency response is achieved from the given input signal.

B Adaptive Filter

An adaptive filter is a filter that self-adjusts its intensity transfer function according to an optimization algorithm driven by an error signal. Because of the complexity of the optimization algorithms, most adaptive filters are digital filters. The adaptive filter reduces the mean squared error between primary input (ECG signal) and the reference input (noise with ECG signal) [18]. The power line interference (50Hz) from ECG signal can be removed by adaptive filtering while its harmonics and high frequency noise can be removed by implementing general notch rejection filters. A non-adaptive filter has a static transfer function while Adaptive filters can be used in applications where some parameters of the desired processing operation are not known in advance. The adaptive filter uses feedback in the form of an error signal to refine its transfer function to match the changing parameters. A filter can be used to re-move the noise, extract information signals and separate two or more combined signals. if the a signal x(k) is processed in a discrete system the output signal will be y(k), if this output signal y(k) is different from the original signal x(k) then it must be needed to modify the system to get the required output.

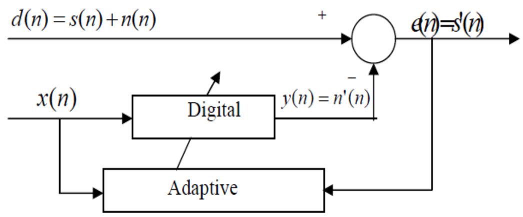

Fig. 2. Adaptive Filter.

Then digital filter will be the solution to ma-nipulate this problem. Digital filters are extremely used in noise cancellation, echo cancellation and also in the field of biomedical engineering to remove unwanted noise from ECG.

Steps of Proposed Method

(i) Firstly read MIT-BIH ECG data files ([100.atr, 100.dat, 100.hea] ………..)

(ii) Extract Features of read data file*x* (ECG), then processed it as stored in MAT file format like ecgdata100.mat, ecgdata104.mat, ecgdata106.mat, ecgdata109.mat and so on.

(iii) Define value of *F[], A[], N* then apply remz() basic filter process // *N* = max sample length (taken 1024)

(iv) Apply DWT transformation in selected MAT ecgdata*.mat processed file.

(v) Precede it for analyzing visualization level of the basis of the LL band of DWT process.

(vi) Since the ECG sample *mydata* is signed as well as unsigned 8-bit mixed type (the most common situation), values vary from 0 to 255 to each containing cell.

(vii) Apply decompositions on the basis of signal quality, noise level then precede it.

- Approximation coefficient storage.
- Horizontal detail coefficient storage.
- Vertical detail coefficient storage.
- Diagonal detail coefficient storage.

(viii) Convert unrecognized values to unsigned 8-bit data.

(ix) Apply Adaptive intensity transfer function on different intensity levels of the decomposed ECG layers and stored it as *SMTn_out*.

(x) *On SMTn_out,* apply kernel function to filter an ECG layers after weighted map and smoothening (*SMTn_out)*.

(xi) The inverse DWT is applied on ECG layers fusion of the layered and HH, HL, LH bands to get the noise free data.

(xii) Process all decomposed and layered ECG's to DTCWT fusion block to compose all resultant as single noise free improved ECG and stored it as *ECG_NF*.

(xiii) Apply IWPT to inversed processed sample data.

(xiv) Finally measurement the following standard parameters as a result: MSE, PSNR, PRD

err = (sum(*x*- *ECG_NF*).^2)/N;
er1 = size (err);
MSE=sqrt(err);
ms = size(*MSE*);
PSNR = 10*log10(*N/MSE*);
PRD = sqrt(*MSE*/sum(*x*.^2)*100);

IV. EXPERIMENTAL RESULTS

This section shows the experimental results of our proposed work. The implementation of the proposed work is done using MATLAB and wavelet toolbox. The comparison of the work is done among different performance metrics like PSNR, MSE and PRD.

A. ECG Database

The Database has been prepared from the MIT-BIH Arrythmia Database directory of ECG Signals from Phyionet Bank, where the source of ECG signals is Beth Israel Hospital Arrhythmia Laboratory [5]. The database contains 48 records. The database is described by – a text header file (.hea), a binary file (.dat) and a binary annotation file (.atr). Header file describes the detailed information about the number of samples, sampling frequency, format of the ECG signal, type and number of ECG leads, patient's history and the other clinical information. In Binary Data file (.dat), the signal is stored in 212 formats. The Annotation file contains the beat annotations.

B. Performance Metrics

1) Percent Root Mean Square Difference (PRD): One of the most difficult problems in ECG compression applications and reconstruction is defining the error criterion. The purpose of the compression system is to remove redundancy and irrelevant information. Consequently the error criterion has to be defined so that it will measure the ability of the reconstructed signal to preserve the relevant information. Since ECG signals generally are compressed with lossy compression algorithms, a way of quantifying the difference between the original and the reconstructed signal, often called distortion.

The most prominently used distortion measure is the Percent Root mean square Difference (PRD) [19] that is given as follows:

$$PRD = \sqrt{\frac{\sum_{n-1}^{N}[(x(n) - \tilde{x}(n)^2]}{\sum_{n-1}^{N}[x(n)]^2}}$$

2) Mean Square Error

The Mean Square error (MSE) of original signal and de-noised signal is given by the following Equation:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(S_{original} - S_{denoised}\right)^2$$

3) Signal to noise ratio

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation and it is calculated as:

$$PSNR = 10 * log10(\frac{N}{MSE})$$

C. Result Analysis

The de-noising algorithm of the proposed methodology is implemented in MATLAB toolbox. The original ECG signal is shown in figure 3 from MIT-BIH arrhythmia database (116). Figure 4 shows the ECG signal of band stop filter and low-pass filter from MIT -BIH arrhythmia database (116).

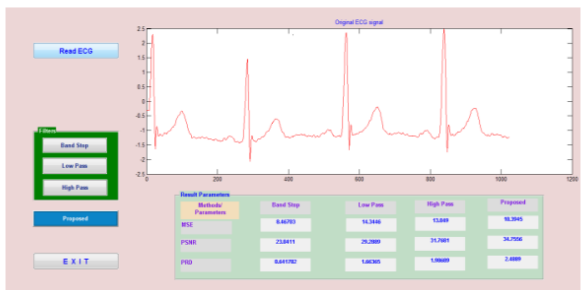

Fig. 3. Original ECG signal image for MIT -BIH arrhythmia database (116).

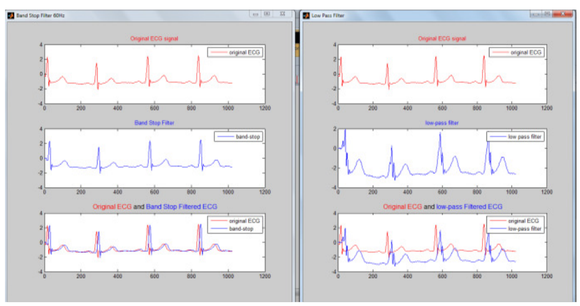

Fig. 4. Band Stop ECG signal image for MIT -BIH arrhythmia database (116).

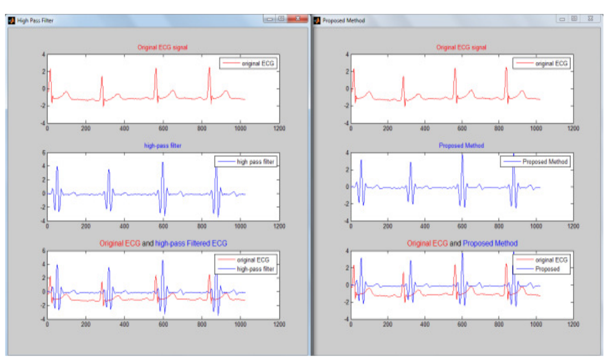

Fig. 5. Band Stop ECG signal image for MIT -BIH arrhythmia database (116).

Figure 5 shows the ECG signal of the high pass filter and proposed method from MIT -BIH arrhythmia database (116). Figure 6 shows the original image from MIT-BIH arrhythmia database (234). Figure 7 shows the ECG signal of band stop filter and low-pass filter from MIT -BIH arrhythmia database (234). Figure 8 shows the ECG signal of the high pass filter and proposed method from MIT -BIH arrhythmia database (234). In this the corrupted signal is removed using kernel adaptive transfer function and DWT wavelet transform whose results for band stop, Low pass, High pass filter and proposed methodology is shown in Table 1, Table 2 and Table 3 for the measuring parameter MSE, PSNR and PRD and the comparative analysis of these metrics is shown through graph.

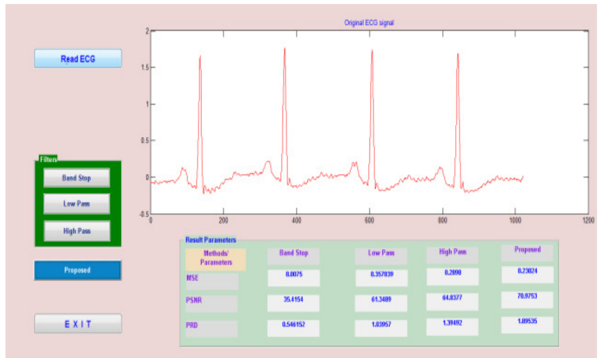

Fig. 6. Original ECG signal image for MIT -BIH arrhythmia database (234).

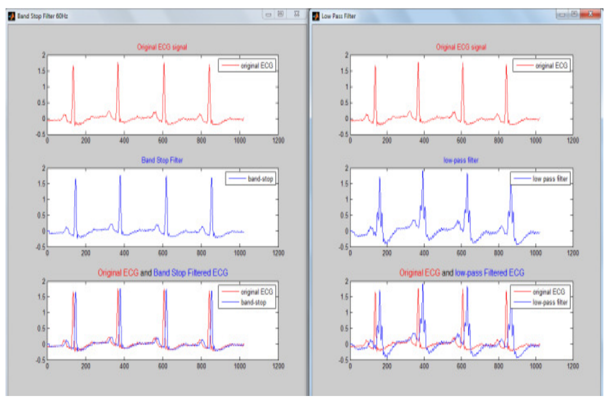

Fig. 7. Band Stop ECG signal image for MIT -BIH arrhythmia database (234).

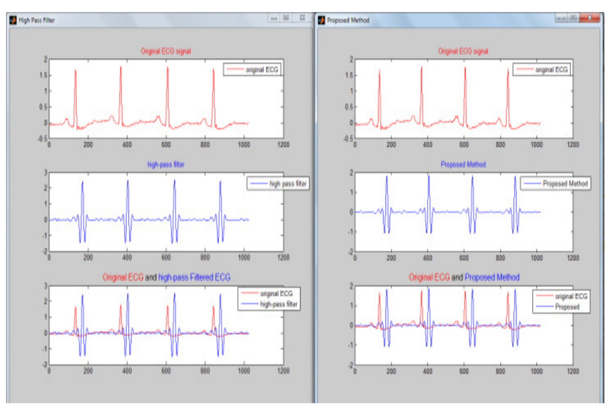

Fig. 8. Band Stop ECG signal image for MIT -BIH arrhythmia database (116).

Table 1: MSE Comparison of Existing methods with Proposed Method.

DataFile/Method	Band Stop Filter	Low Pass Filter	High Pass Filter	Proposed Method
100.dat	8.14266	4.83684	4.38233	3.2589
104.dat	8.01766	3.52147	3.05725	2.40145
106.dat	8.11859	2.3815	2.24183	1.70258
109.dat	8.30172	8.06264	7.42155	5.8254
114.dat	8.105	3.30033	3.00076	2.0698
116.dat	8.46703	14.3446	13.049	10.3945
220.dat	8.17484	9.97797	8.86095	7.06852
234.dat	8.0075	0.357839	0.2898	0.23024

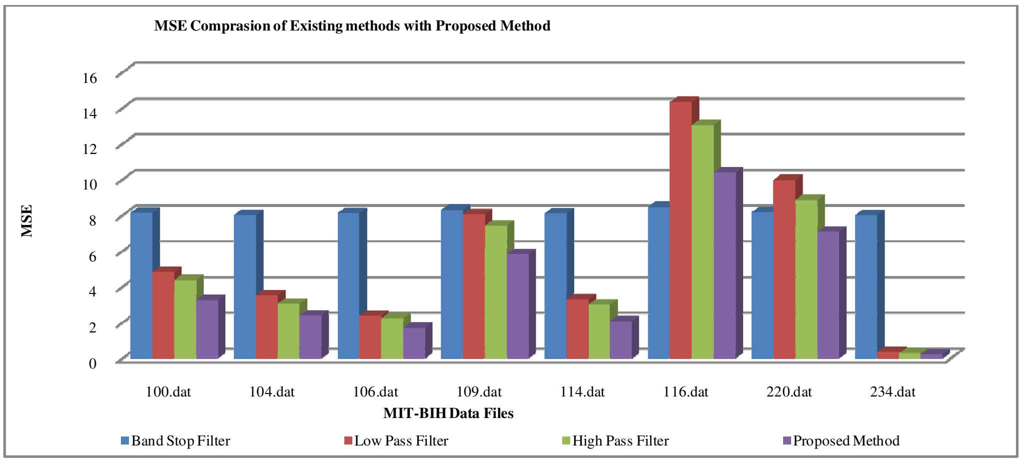

Fig. 9. Comparison of the existing method with proposed method for MSE.

Table 2: PSNR Comparison of Existing methods with Proposed Method.

DataFile/Method	Band Stop Filter	Low Pass Filter	High Pass Filter	Proposed Method
100.dat	26.5932	38.7914	41.2456	46.256
104.dat	32.851	41.4882	44.373	48.985
106.dat	27.1465	44.8857	47.0676	51.9825
109.dat	24.3496	34.2931	36.6698	40.258
114.dat	27.5111	42.0515	44.535	48.952
116.dat	23.0411	29.2889	31.7681	34.7556
220.dat	25.9838	32.4418	35.13	38.5002
234.dat	35.4154	61.3489	64.8377	70.9753

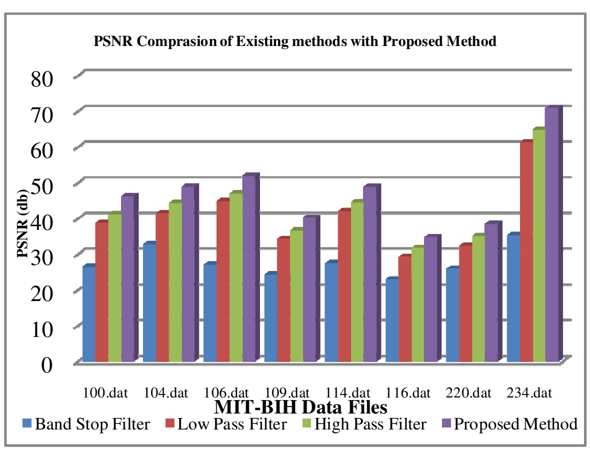

Fig.10. Comparison of the existing method with proposed method for PSNR.

Table 3: PRD Comparison of Existing methods with Proposed Method.

DataFile/Method	Band Stop Filter	Low Pass Filter	High Pass Filter	Proposed Method
100.dat	0.775836	2.96973	3.1141	3.7
104.dat	0.56975	2.64711	2.78658	3.366
106.dat	0.732877	1.98415	2.29445	2.79636
109.dat	0.708295	2.08995	2.36723	2.87076
114.dat	0.878565	3.76083	3.80434	4.3079
116.dat	0.641782	1.66365	1.98689	2.4889
220.dat	0.632701	2.16032	2.39511	2.89706
234.dat	0.546152	1.03957	1.39492	1.89535

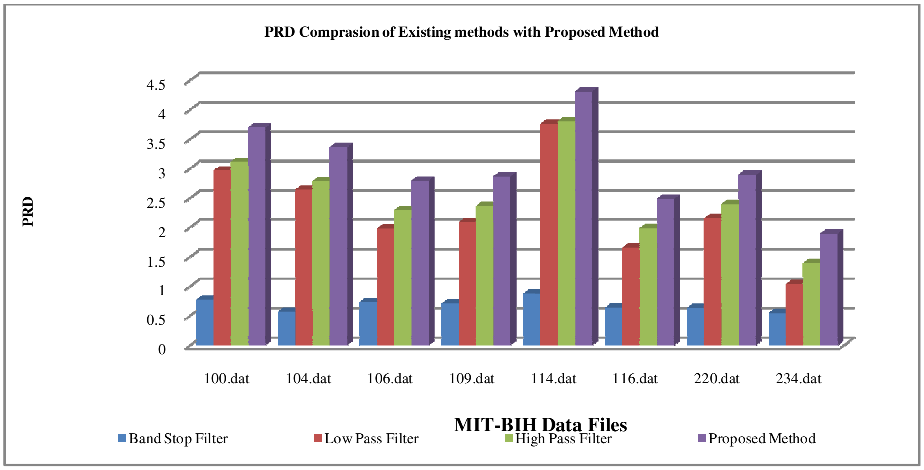

Fig. 11. Comparison of the existing method with proposed method for PRD.

In table 1, the result of proposed method for the MSE measuring parameter is 0.23024 and the exiting method is .2898 which is improved result and the analysis between these methods is shown through graph in figure 9. Similarly, in table 2, PSNR result of proposed method is 70.9753 and existing method is 64.8377, it means that proposed method is efficient in reducing the noise from the ECG signal which is shown in figure 10. Table 3, shows the result for the PRD parameter, the value for the proposed method is about 1.89535 while for existing method is 1.39492.The comparative analysis is shown through graph in figure 11. After analysis it is found that our proposed method gives better results than the existing method and it means this method effectively de-noising the ECG signal.

V. CONCLUSION

To keep the ECG signal free from the noise and distortion is tedious task and it is very essential to get clear ECG signal for diagnosing the disease effectively. Lots of work has been done to de-noise the ECG signal completely but they are not much effective. In this paper, we use DWT wavelet transform using kernel adaptive filter to de-noise. In signal de-noising proposed method gives better results than the existing method and from simulation results, it is analyze that discrete wavelet transform with adaptive filter can remove the noise from the signal effectively and enhance the PSNR, MSE and PRD. The main benefit of wavelet transform based de-noising is that it can effectively retain the amplitude and frequency of the original signal than other method. The experimental result of the proposed method is better than the existing de-noising method in the aspect of retaining geometrical characteristic and enhancement in the PSNR, MSE and PRD.

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