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Performance Evaluation of ECG Signal Denoising & QRS Peak Detection for Cardiac Abnormalities

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Abstract: Cardio attacks are the primary cause of most deaths in these days. To accomplish a quick and accurate diagnosis and to provide the functional activity of the heart, Electrocardiogram (ECG) signal is used in biomedical field. The QRS complex is the most important component within the ECG signal. QRS peak detection is complex due to the wide range of ECG waveforms and various types of noise incurred. In this paper we present an automated scheme using wavelet filtering techniques. A four-level biorthogonal spline wavelet transform is used for QRS complex detection. Further it is enhanced by using matched response filter to improve statistical parameters. A noise evaluation method is used to quantify the noise amount and to select a lower – noise wavelet signal. The QRS peaks can be detected by the extremum pairs in the selected wavelet detail signal for the better parametric values. Results prove that our experiment gives better results than other algorithms.

Keywords— ECG, Detection Error Rate, MIT-Arrhythmia database, Positive Prediction Value, Sensitivity, Thresholding and Wavelet Transform.

I. INTRODUCTION

The analysis of ECG signal is to locate the R-peak accurately. ECG signals are usually contaminated by various noises such as PLI(Power Line Interference), contact noise, patient– electrode motion artifacts, electromyographic noise, baseline drift etc. Accurate detection of R peak is a challenging task because of the presence of noise and the varying morphologies of ECG waves.

Chun-Cheng et al. proposed a novel algorithm to detect QRS complex peak in ECG signal and evaluated the algorithm on MIT BIH MIT-Arrhythmia data base [14] in terms of Sensitivity (Se), Positive Prediction Value (PPv), and Detection Error Rate (DER). The proposed algorithm gives better results than existing techniques [1]. U. Rajendra et al. worked on R peak detection using Convolutional Neural Networks (CNN) with deep learning concept by considering 11 layers and this algorithm can accurately detect the unknown ECG signals even with noise [2]. Acharya, et al compared various denoising techniques such as Empirical Mode Dec omposition (EMD), Discrete Wavelet Transform (DWT) and Discrete Cosine Transform(DCT) to get the coefficients then these coefficients are reduced by using Locality Preserving Projection Method and then fed to K Nearest Neighboring (KNN) Classifier to achieve best classification[3]. To detect and localize myocardial infraction in ECG signal, Sharma et al. proposed a novel technique on Multi Scale Energy and Eigen Space (MEES). Support Vector Machine (SVM) with both linear and radial basis function (RBF) kernel and KNN are used as classifier [4]. Liu et al. developed a novel ECG parameterization algorithm in MI detection which gives better accuracy than existing techniques[5]. Safdarian et al. worked on the detection and localization of MI in left ventricle of heart. In this article the author used pattern recognition method to get good accuracy for ECG signal classification [6]. Banerjee et al presented a method using Cross wavelet Transform and Wavelet Coherence to analyze ECG signal [7]. Arif et al. worked on an automated detection and localization of MI using KNN classifier which gives high accuracy and very helpful for diagnosis of MI [8]. Li Sun et al. worked on both (MIL) Multiple Instance Learning and new strategy MIL called latent topic MIL to classify ECG signal. Proposed algorithm has evaluated on PTB diagnostic database and it improves the quality of classification in terms of sensitivity and specificity [9]. Medical image analysis and video quality assessment which gives better results than other existing techniques [13].

Figure 1 shows that the flow graph of the proposed approach for the detection of the QRS complex. The purpose of the signal preprocessing is to segment the ECG recording and remove the baseline drift. This article describes about signal preprocessing and QRS peak detection using four-level dyadic wavelet transform

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II. RELATED WORK & PRELIMINARIES

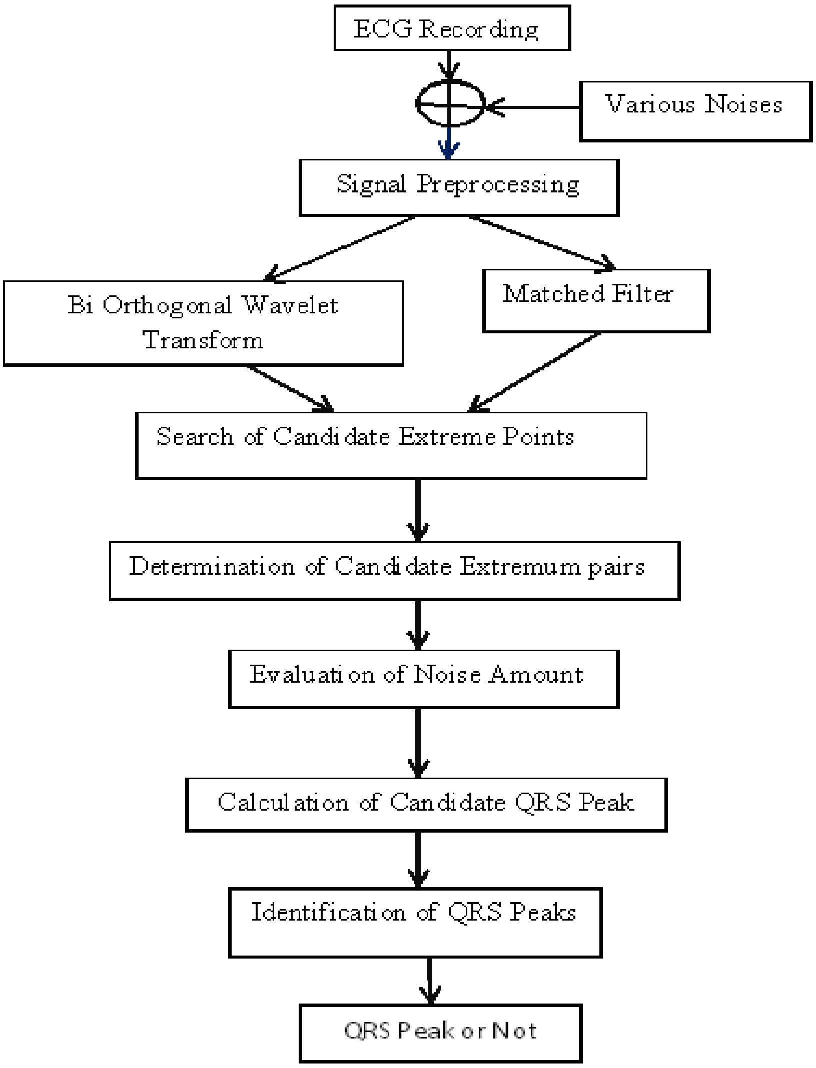

Fig. 1: Flow graph of Proposed Approach

III. METHODOLOGY

The proposed technique includes preprocessing of ECG waveforms by removing baseline drift using Biorthogonal Wavelet Transform and Matched Response Filter.

Step 1: Read the ECG samples from MIT-BIH database.

Step 2: Add various noises such as AWGN, Baseline Wander and Power Line Interference to the original ECG sample individually to get noisy data.

Step 3: Decompose the noisy data by using Biorthogonal Wavelet Transform for '4' levels, which gives Approximation and Detailed coefficients of different lengths.

Step 4: Find the positive and negative extreme points using the detailed coefficients d2, d3 and d4.

Step 5: Divide the extreme detail signals into four subsections and then calculate positive and negative threshold TH+ and TH- using the following equations

$$TH+=\frac{1}{4}\times\frac{(M_{Max,1}+M_{Max,2}+M_{Max,3}+M_{Max,4})}{4} \quad (1)$$

$$TH-=\frac{1}{4}\times\frac{(M_{Min,1}+M_{Min,2}+M_{Min,3}+M_{Min,4})}{4} \quad (2)$$

Where $M_{Max,k}$ and $M_{Min,k}$,k=1,2,3,4 denote points for the four subsections.

Step 6: Search the candidate extreme point with values larger than the positive threshold, $TH+$, or smaller than the negative threshold $TH-$.

Step 7: Apply Matched Response filter to detect the QRS peaks instead of wavelet transform.

Step 8: Compare the results by evaluating the parameters Sensitivity (Se), Positive prediction value(Pp) and Detection Error Rate(DER) using the following equations

$$Se(\%)=\frac{TP}{TP+FN}\times 100\% \quad (3)$$

$$PPV(\%)=\frac{TP}{TP+FP}\times 100\% \quad (4)$$

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$$DER(\%) = \frac{FP + FN}{Total\ no\ of\ beats} \times 100\% \qquad (5)$$

where TP is the number of true positive peaks (QRS peaks detected as QRS peaks), FN is the number of negative peaks(QRS peaks detected as Not QRS peaks) and FP is the number of false positive peaks (Not QRS peaks detected as QRS peaks).

IV. RESULTS AND DISCUSSIONS

This article presents the comparative analysis of wavelet based approach and Matched Filter response to eliminate various noises like Baseline Wander, Power Line Interference and Additive White Gaussian Noise in ECG signal. Sample ECG data is collected from MIT BIH Arrhythmia Database [11]. It consists of a collection of ECG data records with sampling rate 360 Hz, 11 bit resolution over 10 mV range. Figure 2 shows that the original ECG data 100m. In this paper noisy signal is generated by adding BW noise and it is shown in Figure 3. Now four level wavelet decomposition is applied for the removal of noise and QRS peaks are detected using DWT which is clearly observed in Figure 4 and its region is shown in Figure 5.

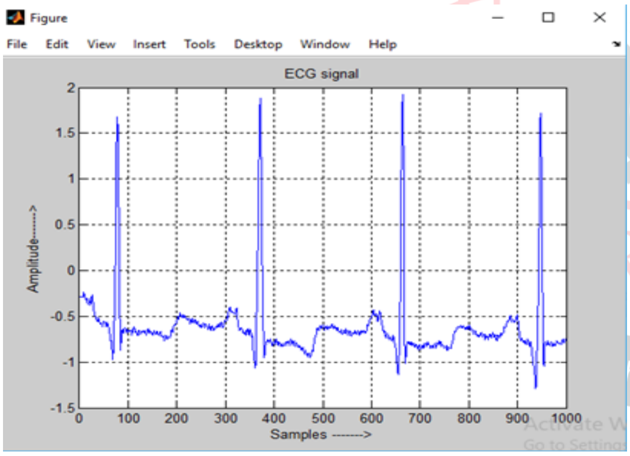

Fig. 2: Raw ECG data of record of sample 100m

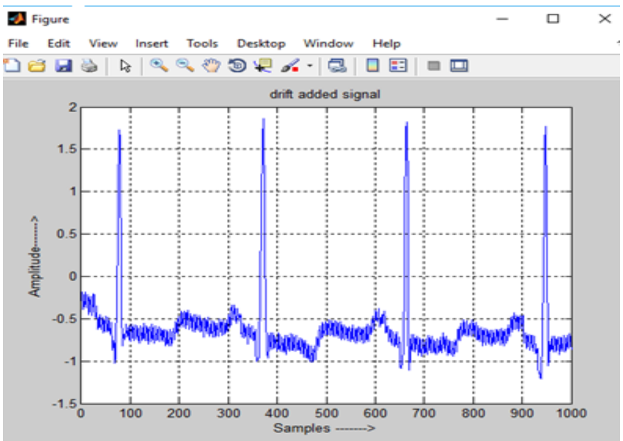

Fig. 3: Noisy ECG Signal

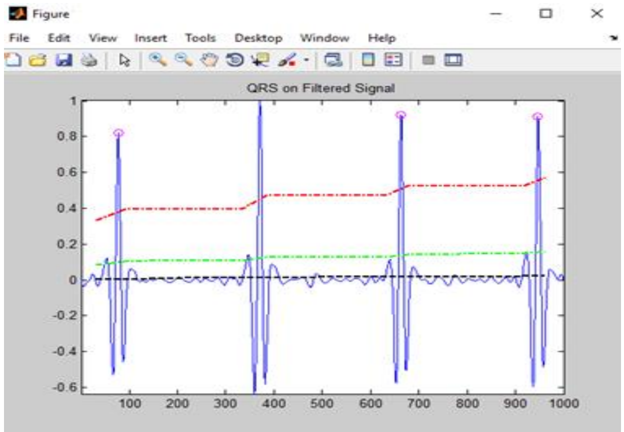

Fig. 4: QRS peaks Detected ECG signal DWT

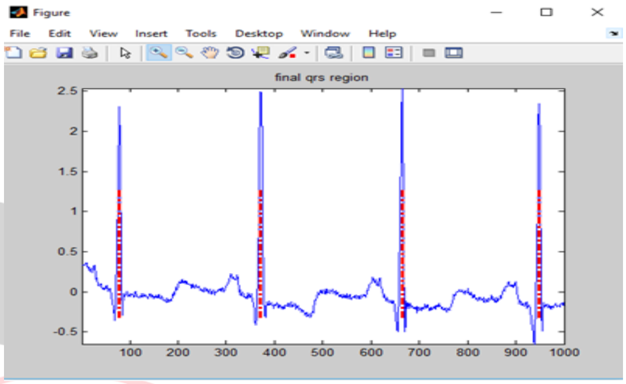

Fig. 5: QRS region on ECG Signal using DWT

Table I:Results of DWT

BW Noise						
Signal	Se	PPV	DER	FP	FN	TP
100m	99.1	99.744	1.154	2.543	9	991
104m	99.3	99.722	0.976	2.765	7	993
105m	98.7	99.701	1.595	2.954	13	987
119m	97.8	99.361	2.828	6.208	22	978
208m	99.5	99.603	0.896	3.962	5	995
Average	98.8	99.626	1.490	3.687	11	989
AWG Noise						
Signal	Se	PPV	DER	FP	FN	TP
100m	99.6	99.709	0.690	2.901	4	996
104m	99.2	99.715	1.083	2.833	8	992
105m	98.6	99.689	1.707	3.049	14	986
119m	97.5	99.366	3.121	6.215	25	975
208m	99.3	99.595	1.103	4.035	7	993
Average	98.8	99.611	1.541	3.807	11	988
PLI Noise						
Signal	Se	PPV	DER	FP	FN	TP
100m	99.6	99.718	0.681	2.814	4	996
104m	98.7	99.730	1.566	2.664	13	987
105m	99.2	99.680	1.117	3.176	8	992
119m	97.5	99.368	3.120	6.2	25	975
208m	99.4	99.587	1.011	4.113	6	994
Average	98.8	99.617	1.499	3.793	11	989

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The average values of Se, PPV, DER, FP, FN and TP for 5 samples 100m, 104m, 105m, 119m and 208m of data is taken and compared in Table I for BW, AWGN and PLI noise removal cases using DWT and its comparative analysis in terms of Se, PPV and DER is clearly observed in Figure 6.

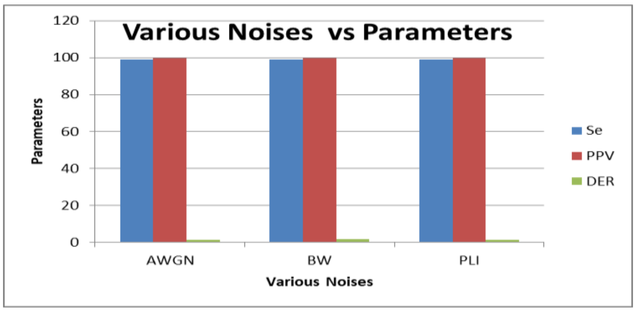

Fig. 6: Various Noises vs parameters

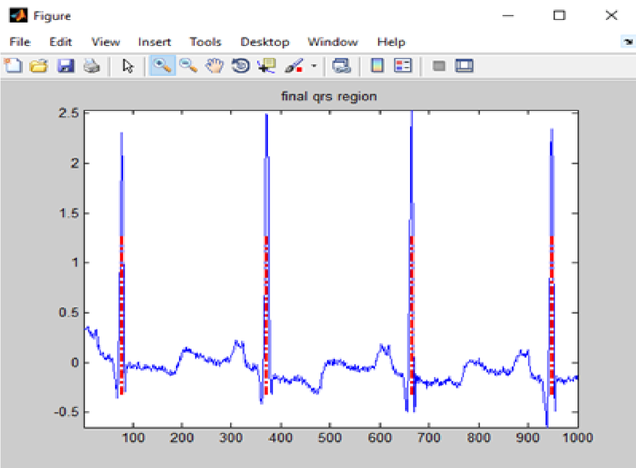

Fig. 8: QRS region on ECG signal using Matched filter

Table II: Results of Matched Filter

BW Noise						
Signal	Se	PPV	DER	FP	FN	TP
100m	99	99.744	1.253	2.535	10	990
104m	99.4	99.713	0.885	2.855	6	994
105m	98.6	99.705	1.691	2.909	14	986
119m	97.5	99.360	3.127	6.273	25	975
208m	99.3	99.610	1.088	3.884	7	993
Average	98.7	99.627	1.609	3.691	12	988
AWG Noise						
Signal	Se	PPV	DER	FP	FN	TP
100m	99	99.744	1.253	2.535	10	990
104m	99.4	99.713	0.885	2.535	10	990
105m	98.6	99.705	1.691	2.535	10	990
119m	97.5	99.360	3.127	6.273	25	975
208m	99.3	99.610	1.088	3.884	7	993
Average	98.7	99.627	1.609	3.552	12	988
PLI Noise						
Signal	Se	PPV	DER	FP	FN	TP
100m	99	99.745	1.253	2.535	10	990
104m	99.4	99.714	0.885	2.855	6	994
105m	98.6	99.706	1.691	2.909	14	986
119m	97.5	99.360	3.127	6.273	25	975
208m	99.3	99.610	1.088	3.884	7	993
Average	98.7	99.627	1.609	3.691	12	988

Figure 7 shows the QRS detection using Matched filter response and its QRS region is shown in Figure 8.

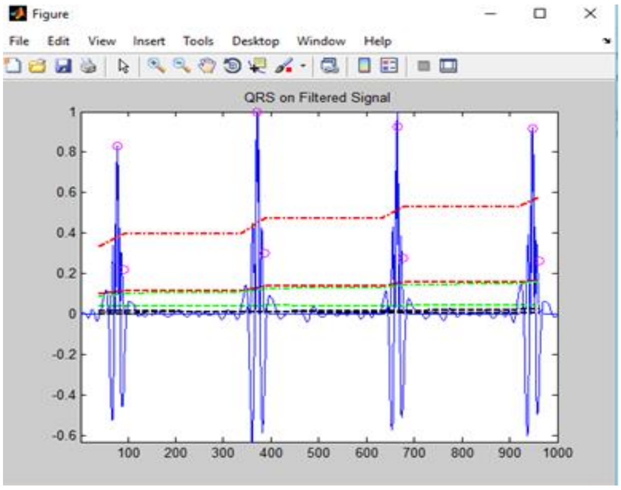

Fig. 7: QRS Detection using Matched filter

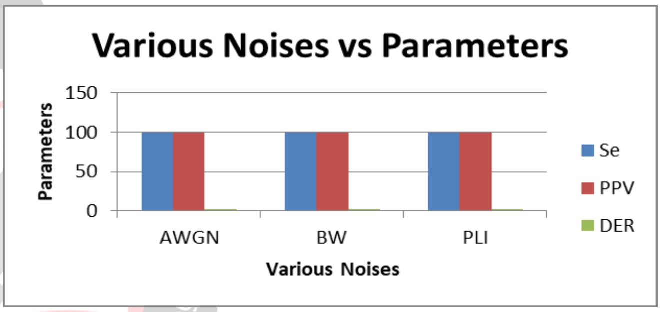

Fig. 9: Various Noises vs parameters

Table II shows that the response of Matched Filter for the average values of five ECG samples and performance is analyzed by using SE,PPV,DER,FP,FN and TP for three noisy cases and it is clearly shown in Figure 9.

V. CONCLUSION

This paper presents a QRS detection algorithm based on a four-level Discrete Wavelet Transform and Matched filter Response. A noise evaluation approach was developed for selecting a lower-noise wavelet detail signal to reduce the noise interference instead of pre-filtering out the high-frequency noise in the signal preprocessing. The identification of QRS peaks was based on the extremum pairs in the selected wavelet detail signals and the proposed decision rules. The proposed technique is able to eliminate BW noise, AWGN and PLI noises to detect QRS peaks and results are compared with Matched Filter Response which gives

enhanced signal but the performance of DWT is better than that of several methods in terms of Detection error Rate, Sensitivity and Positive Prediction Value. This work can be extended by changing the thresholding with advanced techniques to enhance the ECG signal.

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