A Robust R-peak Detection Algorithm using Wavelet Packets

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ABSTRACT
The efficient detection of R-peaks in electrocardiogram (ECG) signal is extremely important for its further processing with regard to cardiac health monitoring. In this paper, an efficient R-peak detection algorithm based on wavelet packets has been proposed. The wavelet packets decompose ECG signal into different frequency subbands of uniform bandwidth. The features evaluated from a set of subbands are combined with heuristic detection strategy for beat detection. The proposed R-peak detection algorithm was tested on different data records of standard data bases Fantasia database, MIT-BIH arrhythmia database and self-recorded signals. A sensitivity S_e= 100% and a positive predictivity of +P = 100% for Fantasia database and S_e= 100%, +P = 100% for self-recorded signals and S_e = 99.94%, +P = 99.93% for MIT-BIH arrhythmia database were achieved using this proposed algorithm.

Keywords
R-peak detection, ECG, Wavelet packets, sensitivity, positive predictivity.

1. INTRODUCTION
The ECG signal is a recording of electrical activity of heart. A single ECG cycle consists of P, Q, R, S, and T waves. The QRS complex and especially R-peak detection is the most prominent feature in the ECG signal and its accurate detection forms the basis of extraction of other features and parameters from ECG signal. Since the QRS complex varies with different cardiac health conditions, therefore efficient and automatic detection of QRS complex and R-Peak is essential for reliable health condition monitoring. Many algorithms have been developed during the last five decades for accurate and reliable detection of R-peaks in the ECG signal indicating high percentages of correct detection, which are classified as syntactic, non-syntactic, transformative and hybrid algorithms. The earlier QRS complex detection algorithm involve a pre-processor stage, where the ECG signal is transformed to accentuate the QRS complex, and a decision stage, where a QRS complex is detected using thresholding, yielded 99.3% detection accuracy [1]. This was further improved to a detection accuracy of 99.67% [2]. A QRS detection algorithm using hardware filter banks was proposed which reported sensitivity of 99.59 % and positive predictivity of 99.56 % against the MIT-BIH Arrhythmia Database [5]. A wavelet transforms based QRS detection algorithm was proposed which reported 0.15 % false detections [7]. A new wavelet based QRS detection algorithm was developed which yielded very high detection accuracy of 99.99% [6]. In the present work a R-peak detection algorithm based on wavelet packets has been proposed. The wavelet packets based algorithm decomposes the ECG signal into different frequency subbands. Features which are indicative of QRS complex is designed by combining a set of subbands. These frequency bands are then combined to give the overall beat detection, in contrast to a single channel analysis as in case of WT-based R-peak detection algorithm. The proposed WP-based QRS detection algorithm was tested on standard databases and self recorded signals. The algorithm was implemented in MATLAB.

2. METHODOLOGY
2.1 Signal analysis using wavelet packets
The analysis of signal using discrete wavelet transform (DWT) is done at different frequency bands with different resolutions by decomposing the signal into approximate and detail information through its filter bank consisting of low pass and high pass filter. The signal is down sampled by a factor of 2 at each level and this process is known as subband coding and it can be repeated for further decomposition of the signal as per requirement. This phenomenon of DWT implementation is illustrated by Figure.1 The wavelet packet decomposition is a generalization of wavelet decomposition which leads to more accurate signal analysis. Wavelet packets are waveforms indexed by three parameters of position, scale and frequency. In orthogonal wavelet decomposition process, the generic step splits the approximation coefficients into approximation coefficients and detail coefficients. The information lost between two successive approximations is captured in the detail coefficients. The next step is splitting the approximation coefficient vector of previous decomposition into detail and approximation coefficients. In corresponding wavelet packets based analysis; each detail coefficient vector is also decomposed into approximate and detailed coefficient vector similar to that in approximation vector splitting. This enables more accurate extraction of intended features of the signal.

2.2 The Proposed R-peak detection algorithm
The efficient detection of R-peak in ECG signal is extremely important for ECG signal feature extraction which leads to highly accurate cardiac health prognosis. The flowchart of the proposed R-peak detection algorithm has been shown in Figure 2. The details of each stage of the proposed algorithm have been described in the following sections.

2.3 The ECG signal Decomposition into frequency subbands using wavelet packets
The proposed R-peak detection algorithm based on wavelet packets decomposes the input ECG signal into different frequency subbands of uniform bandwidth. The subbands are downsampled by a factor of 2 at each level. The decomposed subbands provide information from various frequency ranges. The number of levels by which the input ECG signal is to be

decomposed, depends on sampling frequency of the input signal.

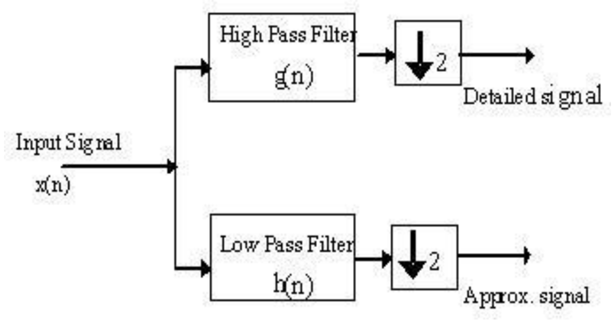

Fig 1: Implementation of DWT

For example in case of MIT-BIH Arrhythmia database signals, the sampling frequency is 360 Hz. So, it is to be decomposed upto five levels as shown in Figure 3. In this case, the input ECG signal is decomposed into 32 frequency bands each having a bandwidth of 5.62Hz. In case of Fantasia database the sampling frequency is 250Hz. Thus, the signal is decomposed upto four level only, which gives 16 frequency bands each of bandwidth 7.75Hz. Similarly, the self-recorded signals which are sampled at 500 Hz are decomposed upto five levels resulting in 32 frequency bands each having a bandwidth of 7.75 Hz. Figure 4 shows an ECG signal and its decomposed frequency bands.

2.4 Combining the subbands for Features extraction

Multiple features are calculated by combining a set of subbands which indicate the QRS complex energy in various frequency bands. A sum-of-absolute values feature is computed using subbands 1and 2.

$$P_1 = \sum_{l=1}^{2} | w_l | \quad (1)$$

The calculated feature P_1 indicates the energy of the ECG signal in the frequency band [5.6, 16.87] Hz. Similarly, P_2 and P_3 are computed using subbands {1, 2, 3, 4}, and {2, 3, 4}, respectively, and these values are proportional to the energy in their respective subbands. A detection logic is used to incorporate some of the above calculated features for accurate location of R-peak in the ECG signal.

2.5 R-peak detection using multiple channels

The objective of the R peak detection algorithm is to determine the accurate location of R-peaks in an ECG signal. In most of the R-peak detection algorithms based on wavelet transform, the input ECG signal is decomposed using DWT upto some appropriate level and then adaptive threshold is applied to the decomposed signal to locate R- peaks [6]. Since QRS complex energy varies with different morphologies and under different cardiac health conditions, therefore instead of using single channel for R-peak detection as in case of WT based algorithms, various frequency subbands are combined in WP based R-peak detection algorithm to enhance the detection efficiency of the algorithm. In WP based R-peak detection algorithm multiple channels with different False negatives (FN's) and False positives (FP's) detections are operated and the results of each are combined together to achieve an overall detection efficiency.

2.5.1 Single channel detection

In single channel detection a computed feature is input to a moving window integrator (MWI) which takes the average of two samples at the downsampled rate. Whenever a feature value is detected as a Signal (noise) peak, the signal (noise) value is stored. The signal (noise) level for each detected event is determined by computing the mean of the previous signal (noise) values using the two equations

N_L= 0.9 ×meanL1 (1)

S_L= 1.1×meanL1 (2)

For each detected event detection strength D_s is determined by comparing with the signal and noise levels (S_L and N_L,) with the feature valve.

$$D_s = \frac{P - N_L}{S_L - N_L}$$

When a feature's value is less than N_L then D_s is set to 0, and if it is above S_L then D_s is set to one. When the D_s of a detected event is greater than a predefined threshold it is categorized as a signal peak and the signal history is updated with the feature's value. When the $D_s$of a detected event is smaller than a predefined threshold it is categorized as a noise peak and the noise history is updated with the feature's value. The D_s thus indicates whether the incoming feature is a signal or noise peak. If detection strength is close to one, then there is a greater possibility that the current peak is a beat, whereas if detection strength is close to zero then there is a greater possibility that the current peak is a noise peak. The detection strength factor is used in the overall R-peak detection logic.

2.5.2 Levels

Multiple channels with different threshold valves are operated on different features in the R-peak detection algorithm to achieve overall detection efficiency.

2.5.2.1 Level 1

In the first level [5] the event detector operated on feature P1 detects a beat whenever there is an inflexion point in the output of MVI. The value of the detected peak is not compared to any threshold; rather it is used to trigger an event in the further levels. This level thus acts as an "event detector," and is used to trigger further logic to eliminate FP's and FN's introduced here.

2.5.2.2 Level 2

This level, consists of 2 single channels (Chan1 and Chan2) operating simultaneously. Both channels use feature P_2 in their respective MWI's, but their respective thresholds are different. Chan1 uses a low threshold ($T_1 = 0.03$) and Chan2 uses a high threshold ($T_2 = 0.7$). When the event detector detects an event, chaneel1 and channel2 are triggered and the output in the MWI's of each of Chan1 and Chan2 are compared with their respective signal and noise levels. The signal (and noise) levels in each channel are computed from the signal (and noise) history of their respective channels. Detection strength for each channel is computed and is compared to their respective thresholds. Each channel classifies the current event as a beat or noise independent of the classification from the other channel. Whenever a channel detects an event (beat or noise peak) its own signal (or noise) history is updated irrespective of the detection status from the other channel.

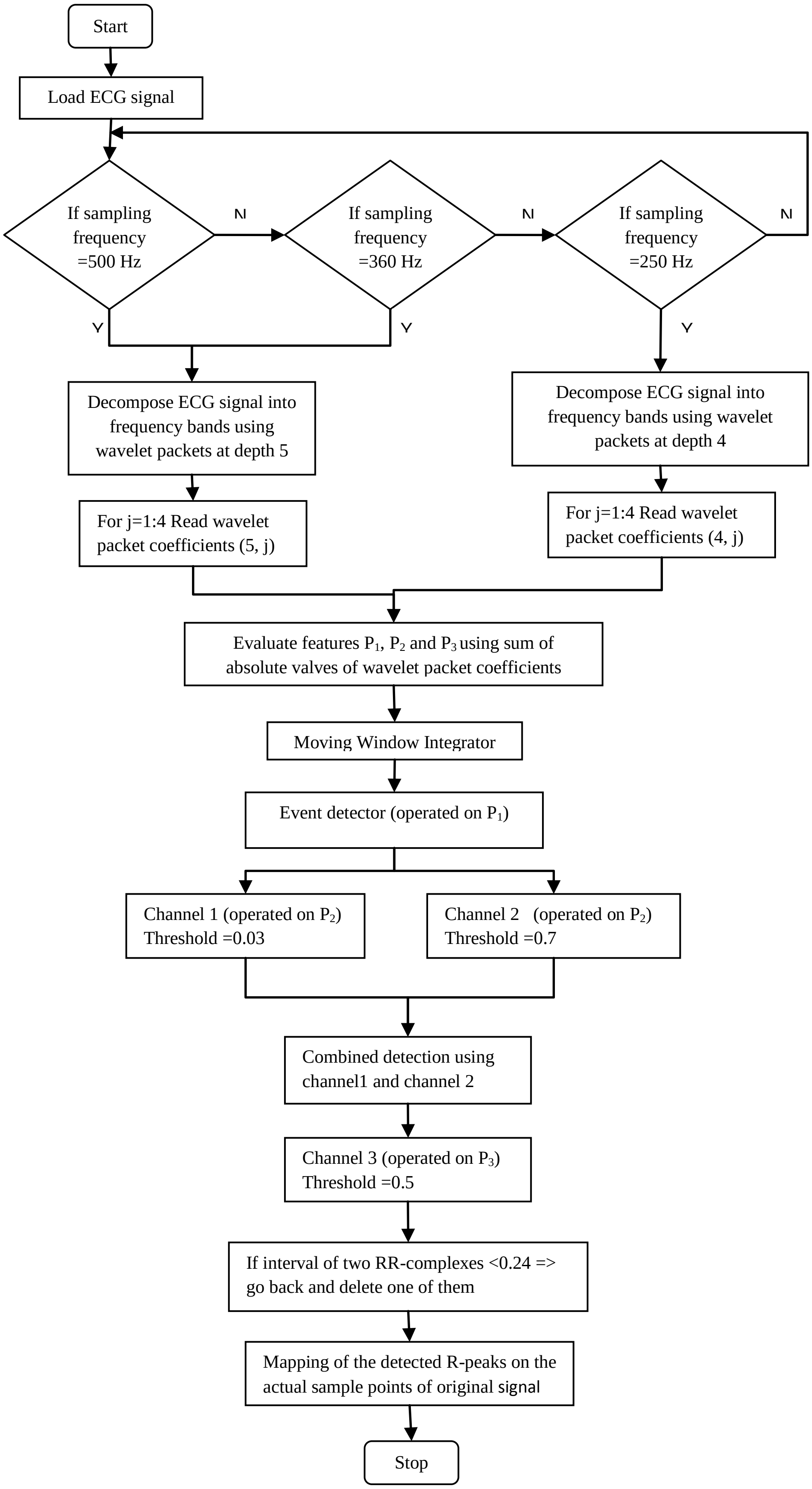

Fig 2: Flowchart of R-peak detection algorithm

In single channel detection, the threshold value determines whether the detected event is a signal peak or noise peak so this valve should be chosen precisely. The algorithm described here is tested for different threshold valves and the specified threshold valves are found to be optimum. This level, thus, operates simultaneously two single channels which have complementary FN and FP detection rates. Chan1 outputs a few FN's but many FP's and Chan2 outputs many FN's but a few FP's. All computations are performed at the downsampled rate and this contributes to the overall computational efficiency of the R-peak detection algorithm.

2.5.2.3 Level 3

This level combines the beat detection classification from each of the 2 single channels in level 2 by including a set of if-then-else rules. The rules incorporate the fact that the 2 single channels have complementary detection rates. Four possible cases arise. If both channels classify the current event as a beat then the output status of level 3 is a beat. Since Chan 2 uses a high threshold, it produces few FP's and, thus, beat detection is very accurate. If both channels classify the current event as a noise peak then the output status of level 3 is a noise peak.

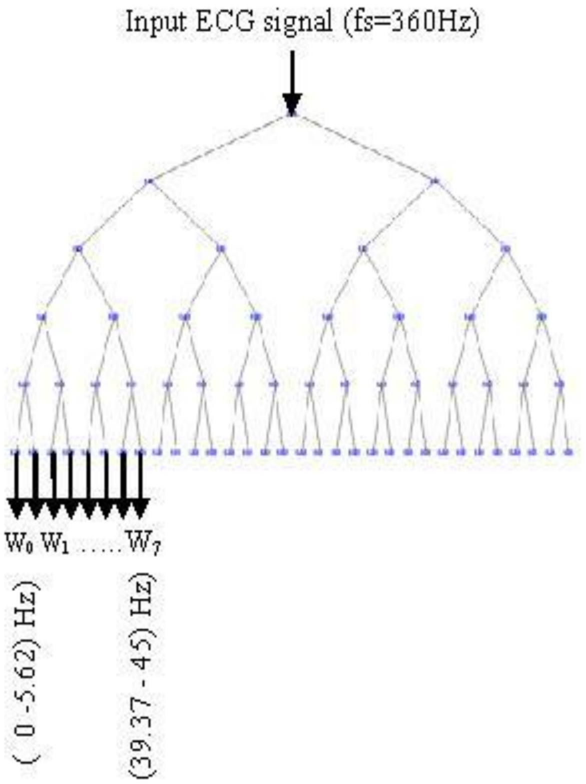

Fig3: Wavelet packet decomposition of the input ECG signal into subbands with uniform bandwidths.

If Chan1 classifies the current event as a noise peak and Chan2 classifies it as a beat then the level 3 classifies the current event as a beat. However, this scenario never appears.

If Chan1 classifies the current event as a beat and Chan2 classifies it as a noise peak, then the detection strengthsD_{s_i}, i={1,2} from each channel are compared. The normalized detection strength

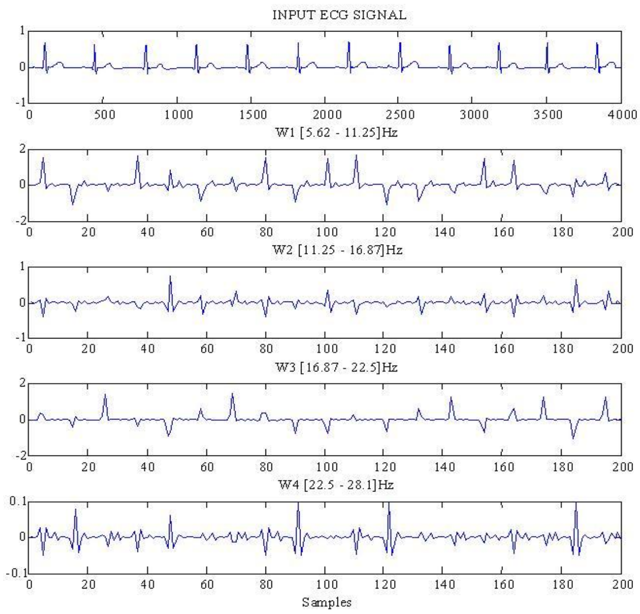

Fig 4: Input ECG signal and its decomposed frequency subbands

indicating which decision was "stronger," is compared to favor the channel with the stronger decision. The detection logic is summarized as follows:

Chan1	✓	×	×	✓
Chan2	✓	✓	×	×
Output	✓	✓	×	Δ_1? Δ_2

WhereΔ_1? Δ_2: if Δ_1> then ✓else ×

$$\Delta_1 = (D_{s_1} - T_1) / (1 - T_1)$$

$$\Delta_2 = (T_2 - D_{s_2}) / T_2$$

(✓: a-beat; ×: a noise peak)

2.5.2.4 Level 4

This level incorporates another single channel and uses feature P_3 as the input to the MWI. If level 3 indicates a-beat, the signal history is updated and the detection status from this level is that the current event is a beat. If level 3 classifies the event as a noise peak, the detection strength of the channel 4 is computed and compared with the threshold ($T_4 = 0.5$ for this channel). If the detection strength is greater than the threshold the current event is classified as a beat and the signal history is updated. If the detection strength is less than the threshold the noise history is updated and the current event is classified as a noise peak. This leads to improved detection rates.

2.5.2.5 Level 5

If a beat was detected during the refractory period (240ms) (with reference to the previous beat detection) and also had minimal detection strength in level 4($D_{s_4} \leq 0.05$), then the status of the event is changed from a-beat to a noise peak. If the interval between two RR complexes is too long a search-back technique is used to look back in time for the QRS complex with low threshold (0.02).

2.6 Mapping of the detected R-peaks on the actual sample points of original signal

The detected R-peaks are fiducial points of the downsampled signal and these are mapped on to the original ECG signal (prior to downsampling) by scanning within a window around the R-peaks (detected in downsampled signal).

3. RESULTS

The performance evaluation of above proposed R-peak detection algorithm was carried out by testing it on standard data of Fantasia database, MIT-BIH arrhythmia database and self-recorded ECG signals [9]. The detection efficiency was described in terms of sensitivity (S_e) and positive predictivity ($+P$), which in turn depends on number of false positive (FP), false negative (FN), and true positive (TP) as shown in equation (2) and (3).

$$S_e = \frac{TP}{TP+FN} \quad (3)$$

$$+P = \frac{TP}{TP+FP} \quad (4)$$

Where, TP is the number of true positives (true detection), FN is the number of false negatives (missed detection), and FP is the number of false positives **(**erroneous detection**).** The sensitivity S_e indicates the percentage of true beats that were correctly detected by the algorithm. The positive predictivity $+P$ indicate the percentage of beat detection which were in reality true beats. The algorithm was tested using different wavelet families in the wavelet packet decomposition tree, the best results were achieved with db2. The test results shown in this paper are based on db2. An overall sensitivity and positive predictivity of 100% was achieved for tested records of Fantasia database and self- recorded signals, whereas sensitivity of 99.94% and positive predictivity of 99.93% was achieved for records of MIT-BIH arrhythmia database tested with this proposed algorithm.

3.1 Test results of Fantasia database

The Fantasia database contains 40 signals, each of 120 minutes duration and sampled at 250 Hz. The algorithm was tested on ten records. Figure 6 and Figure 7 shows the detected R-peaks in record no. f2o01 and f2o05.Table 1 shows the test results of the algorithm on tested records of Fantasia database.

3.2 Test results of self-recorded signals

The lead-II ECG signals in 10 subjects at sampling frequency of 500 Hz were recorded using BIOPAC MP 100 system. Figure 8 shows the test results of the algorithm on subject S1 of the self-recorded ECG signals. Table 2 shows the test results of the algorithm on self-recorded signals.

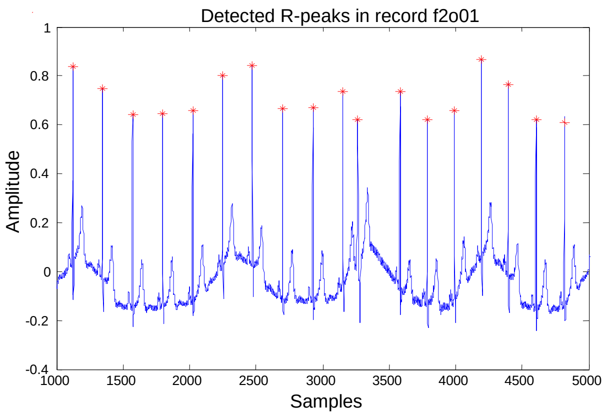

Fig 5: Detected R-peaks in record no. f1o01 from Fantasia database

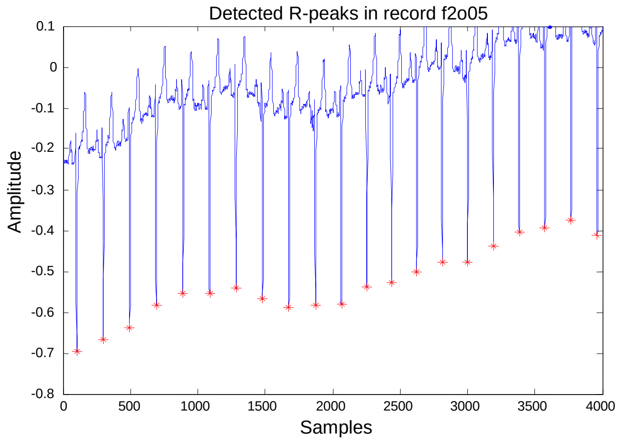

Fig 6: Detected R-peaks in record no. f2o05 from Fantasia database

3.3 Test results of MIT-BIH arrhythmia database

The MIT-BIH arrhythmia database contains 48 records in total, each of 30 minutes duration and sampled at 360 Hz. The R-peaks detection was tested on 20 records of MIT-BIH arrhythmia database. Figure 8, Figure 9 and Figure 10 shows the detected R-peaks in record no. 100, 112, and 231 respectively of the tested ECG signals. Table 3 shows the test results for all tested 20 records of MIT-BIH arrhythmia database.

4. DISCUSSIONS

The test results with proposed wavelet packet based R-peak detection algorithm has shown very high detection efficiency when tested on standard data of Fantasia database, MIT-BIH arrhythmia database and self-recorded database. For ECG records of Fantasia database and self-recorded database, the algorithm has shown 100% detection efficiency. However the algorithm achieves an overall sensitivity of 99.94% and a positive predictivity of 99.93% on the MIT-BIH arrhythmia database as can be seen in Table 3.

Table 1 R-peak detection efficiency evaluation on Fantasia database

Record No.	Actual no. of beats	No. of detected beats	TP	FP	FN	Se	+P
f1o01	392	392	392	0	0	100	100
f1o02	303	303	303	0	0	100	100
f1o04	250	250	250	0	0	100	100
f2o01	339	339	339	0	0	100	100
f2o03	301	301	301	0	0	100	100
f2o04	302	302	302	0	0	100	100
f2o05	347	347	347	0	0	100	100
f2o06	239	239	239	0	0	100	100
f2o07	254	254	254	0	0	100	100
f2o08	320	320	320	0	0	100	100
Total	**2747**	**2747**	**274**	**0**	**0**	**100**	**100**

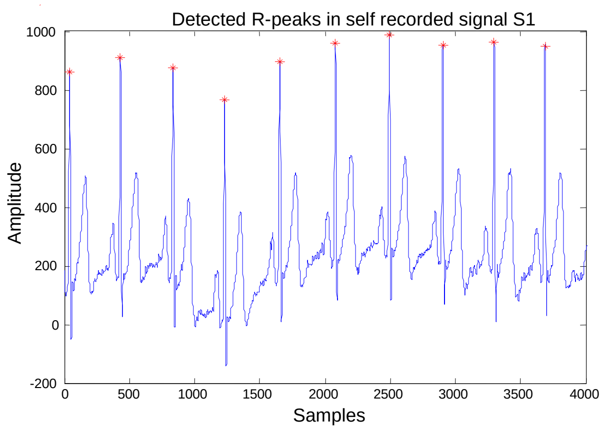

Fig 7: Detected R-peaks in self-recorded signal S1

Table 2 R-peak detection efficiency evaluation on self-recorded signals

Subject	Actual No of beats	No of detected beats	TP	FP	FN	SE	+P
S1	258	258	258	0	0	100	100
S2	199	199	199	0	0	100	100
S3	249	249	249	0	0	100	100
S4	317	317	317	0	0	100	100
S5	281	281	281	0	0	100	100
S6	254	254	254	0	0	100	100
S7	259	259	259	0	0	100	100
S8	245	245	245	0	0	100	100
S9	333	333	333	0	0	100	100
S10	230	230	230	0	0	100	100
Total	**2625**	**2625**	**2625**	**0**	**0**	**100**	**100**

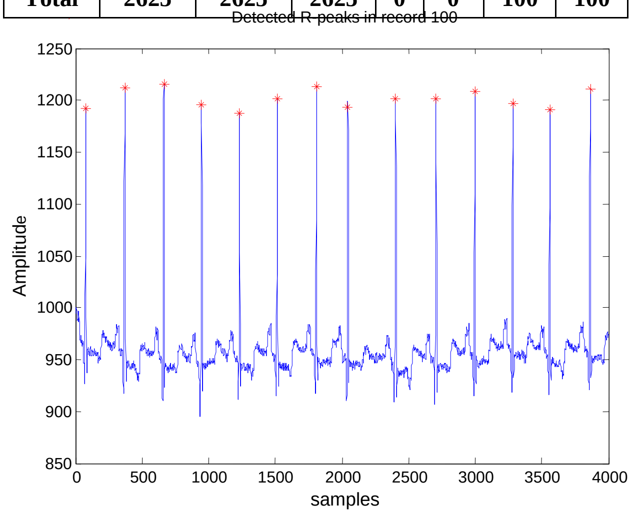

Fig 8: Detected R-peaks in record no. 100 of MIT-BIH arrhythmia database

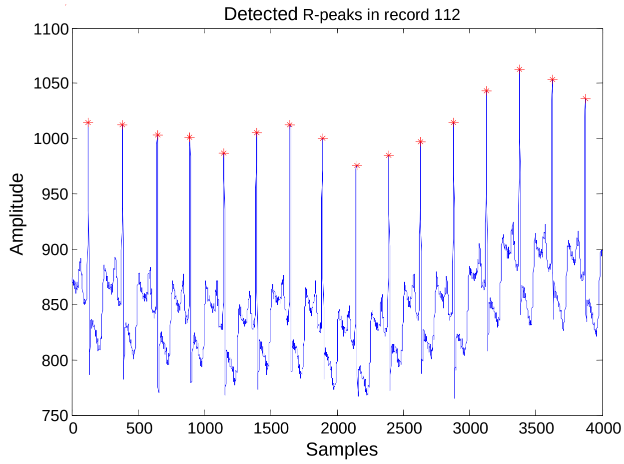

Fig 9: Detected R-peaks in record no. 112 of MIT-BIH arrhythmia database

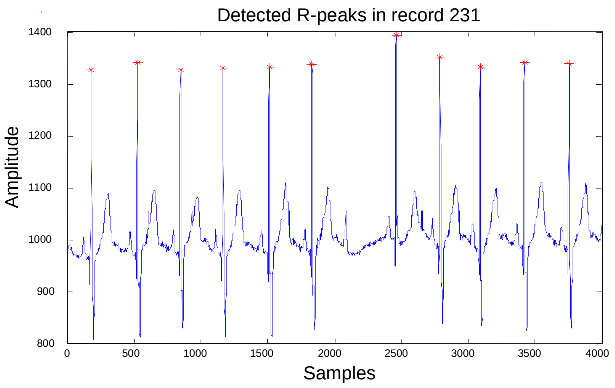

Fig10: Detected R-peaks in record no. 231 of MIT-BIH arrhythmia database

But for many records such as record no. 100, 103, 112, 115, etc. it has was able to correctly locate all the R-peaks on actual positions. The Figure 8 and Figure 9 show the small part of signal for record no. 100 and 112. Thus sensitivity and positive predictivity was found to be 100% for these records. In some of the records, the algorithm fails to detect few beats or detects

Table 3 R-peak detection efficiency evaluation on MIT-BIH arrhythmia database

Record no.	Actual no. of beats	No. of detected beats	TP	FP	FN	Se	+P
100	2273	2273	2273	0	0	100.0	100.0
101	1865	1865	1863	2	2	99.89	99.89
102	2187	2187	2186	1	1	99.95	99.95
103	2084	2084	2084	0	0	100.0	100.0
107	2137	2140	2137	3	0	100.0	99.85
112	2539	2539	2539	0	0	100.0	100.0
115	1953	1953	1953	0	0	100.0	100.0
118	2275	2278	2274	4	1	99.82	99.96
121	1863	1864	1861	3	2	99.89	99.84
122	2476	2476	2476	0	0	100.0	100.0
123	1518	1518	1517	1	1	99.93	99.93

124	1619	1619	1615	4	4	99.75	99.75
205	2656	2657	2652	5	4	99.82	99.79
209	3006	3011	3006	5	0	100.0	99.83
212	2748	2749	2748	1	0	100.0	99.96
215	3363	3366	3363	3	0	100.0	99.91
219	2154	2153	2152	1	2	99.91	99.95
220	2048	2047	2047	0	1	99.95	100.0
231	1573	1571	1571	0	2	99.87	100.0
234	2753	2746	2746	0	7	99.74	100.0
Total	**4509**	**4509**	**4506**	**33**	**27**	**99.94**	**99.93**

some false beats which decreases the detection accuracy of the algorithm. In case of records from the MIT-BIH arrhythmia database and Fantasia data base, the FP and FN were calculated through comparison between the detected beats and the annotated beats. However, for self-recorded signals the FP and FN were calculated from the plots showing the marked peaks on each signal. The proposed WP-based R-peak detection algorithm has the advantage of wavelet analysis since wavelet packets is a more generalization of wavelet transform. Therefore this WP based R-peak detection algorithm is computationally more efficient since it operates at lower sampling rate than the input sampling rate of ECG signal. Moreover, this algorithm is directly applied to raw ECG signal without any prefiltering since the wavelet packets decompose the signal into different frequency bands, thus eliminating the need of a separate filter for pre-processing. Thus the algorithm is highly robust due to implicit filtering by wavelet packets.

5. CONCLUSIONS

In this paper a highly efficient and robust R-peak detection algorithm using wavelet packets has been proposed. The proposed algorithm is computationally efficient since it operates at the subband rate. Instead of using single channel for beat detection, multiple frequency bands with complementary false positives and false negatives are fused together for the overall beat detection. This approach results in high detection efficiency. The R-peak detection algorithm achieves S_e = 100% and +P = 100% on Fantasia database and S_e = 100% and +P = 100% on self-recorded signals. However, it has shown S_e = 99.94% and +P = 99.93% on lead-I of the MIT-BIH arrhythmia database for 45090 beats.

Future work may be extended towards studying the algorithm performance with other wavelet families. Even optimal frequency bands may be worked upon to enhance the peak detection efficiency. This proposed R-peak detection algorithm will result into highly accurate heart rate variability signal, which can have potential to enhance the accuracy in cardiac health prognosis.

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