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An Improved R-Peaks Marking Method Using Fourier Decomposition and Teager Energy Operator

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ABSTRACT

The exact discovery of R-peak becomes very much crucial while extracting prominent features from Electrocardiogram (ECG) signal. However, identification of R-peaks precisely becomes more challenging due to contamination of noise and fragmented QRS complexes. This paper presents an improved method of marking R-peaks. Initially, an efficient Fourier Decomposition Methodology (FDM) is used for removing noise. The accuracy of finding R-peaks can be improved by enhancing the QRS complexes using Teager Energy Operator. Hilbert Transform and Zero Cross Detector (ZCD) are used for marking the R-peaks. The MIT-BIH arrhythmia database is used for validating the proposed scheme and attained 99.97% accuracy, 99.98% of sensitivity and 99.98% of positive predictivity. The findings proved that proposed method is superior as compared to the proven techniques in the literature.

1. INTRODUCTION

The ECG signal is evolved as an extensively used rapid investigation tool to monitor cardiac abnormalities. It can give useful information about the functionality of the cardiovascular system. The threat of cardiovascular diseases is growing in India. The occurrence of cardiovascular diseases in India was estimated to be 5.45 cores in the year 2016 [1]. The ECG signal analyses and accurate detection of feature points take a big part in the identification of cardiac abnormalities. The standard ECG signal consists of five characteristic waves: P wave, Q wave, R wave, S wave and T wave. Ascertaining accurate R-peaks becomes a benchmark for the extraction of remaining all fiducial points [2]. Nonetheless, Morphology of the ECG gets affected owing to the variation in the characteristic waves and noise interference. So, computer-aided diagnosis is required to precisely delineate the R-wave to assist physicians and doctors with appropriate medical intervention. Conventionally, the wave functions were identified by both time and frequency domain signal processing technique [3, 4].

In recent developments, various wavelets transform techniques [5], time-frequency distribution of S-transform [6, 7], Circulant matrix-based continuous wavelet transform [8]. and convolution window [9] was used for ascertain R-peaks. However, correct marking of the R-peaks remains an open problem.

The primary objective of this work is to emphasizing the R wave and suppressing the effect of other wave functions while delineating the R-waves. In this work simple and efficient FDM is used for preprocessing of the ECG signal. The combination of Teager Energy Operator (TEO), Hilbert Transform (HT) and Zero Cross Detector (ZCD) is used for implementing the peak finding Logic. In our proposed work, FDM has applied for denoise the ECG signal by suppressing the BW and PLI. In the subsequent stage, TEO is calculated to enhance the R-waves. At last, Hilbert Transform and Zero Cross Detector are used for reliable estimation of R-waves and its peak positions.

The reminder of the paper has been ordered as follows. We will present the previous research concerning to field of R-peak identification in the second section. Section 3, presented proposed R-peak identification methodology. Performance assessment this work and shown results in Section 4. In section 5 the work is concluded.

2. LITERATURE REVIEW

The reliable finding of R-peaks is the most significant part while extracting characteristics of the ECG signal. Hence numerous R-peak finding techniques are proposed in the literature. At first, identification of the QRS complex was established by Pan and Tompkins [10] using linear filtering and nonlinear processing techniques. Linear filtering composed by high pass and low pass filters is used for attenuate the noise. Differentiation, squaring and moving window integration are employed in nonlinear processing to generate the signal which consists of slope, amplitude and width information of QRS complex. Adaptive thresholds are used for marking the R-peaks in the signal. Hamilton and Tompkins [11] have refined the decision rules to improve the efficiency of marking R-peaks. Later various derivative-based approaches [4-11] have been developed for locating R-peaks. Another method Empirical Mode Decomposition (EMD) decomposes the signal into different functions and process at different frequency ranges [8], but it has a problem of low frequency resolution. Digital filters [12-14] also implemented for the elimination of noise and improving accuracy. These are optimum compared with standard FIR filters. Nonlinear energy operator and simple thresholding technique has also been used for efficient marking of R-Peaks [15-17]. Fractional Stock well transform is a combination of fractional fourier transform and Stockwell transform has been used by Bajaj and Kumar [18]. It becomes a popular tool for analyzing the time varying signals. Shannon Energy Envelope (SEE) is the average spectrum energy, and it is an improved method of marking R-peaks [19, 20]. The quality of the ECG signal determines the proficiency of identifying R-waves and its peaks. Over decades the proposed techniques have mainly two parts: the preprocessing stage and peak finding logic. Preprocessing of the signal is mainly employed for denoising the signal and enhancing the required wave function. For efficient detection of R-peaks, a peak finding method is used. Various preprocessing techniques peak finding methods are described in the literature but reliable identification of R-peaks remains an open challenge. The combination of Fourier decomposition methodology and Teager Energy Operator is used at the preprocessing stage and Hilbert Transform and Zero Cross Detector are used at the second stage for reliable identification of R-peaks.

3. PROPOSED METHOD

The proposed method for accurate identification of R-Peaks is depicted in Figure 1. It consists of four different stages i.e. cleaning of ECG signal, Emphasizing the QRS complex, Peak finding logic and R-peaks detection. Initially, Fourier Decomposition Method (FDM) is applied as a part of preprocessing to remove the noise. The FDM uses DFT and IDFT based zero-phase filter bank, to break down the given signal into multiple frequency bands and regenerate filtered signal from the required frequency components. Furthermore, FDM is the most effective way of cleaning the ECG signal. It can be done by eradicating the BW and PLI [21]. An amplitude normalization and Teager Energy Operator (TEO) is calculated in the second stage to emphasize the QRS complexes. TEO gives instantaneous frequency of the signal and also more sensitive to sudden changes. Initially, it was used for nonlinear signal processing and found many applications in speech signal analysis. It will also reduce the effect of P- peak and T-peak while detecting R-peaks. The generated TEO Signal enhances the R-wave function and plays a significant part in finding the R-peaks in the proposed algorithm. The third stage is designed using the combination of HT and ZCD for detection of R-peaks. Accurate detection of local maxima is possible by finding Zero cross points on the Hilbert Transformation of TEO signal. Finally, the original R-peaks on ECG signal can be detected by projecting zero cross points on to the original ECG signal. The following subsections describe all the stages in detailed.

3.1 Fourier decomposition method for noise suppression

The ECG signals can be distorted by multiple noise sources, which include PLI, BW, electrode contact noise and motion artifacts, etc. Owing to these noises the reliable identification of R-Peaks becomes complicated. Different methodologies are formulated in the literature over the years to remove PLI and BW from the ECG signal. Some of these methods use high pass filters for removing PLI and low pass filters to remove BW. However, these methods generate computational delays and nonlinear phase distortion [22-25]. This can be addressed by exploiting the advantage of Zero phase filter bank [26]. Another popular approach is signal decomposition using discrete wavelet transforms [27-29] for ECG denoising, but noise is present at various levels of detailed coefficients. Thus, removing these coefficients eliminates the noise and sometimes it leads to loss required information also. In this paper, we are using FDM which clearly outperformed all other methods. FDM decomposes the given signal into a set of various frequency bands [21].

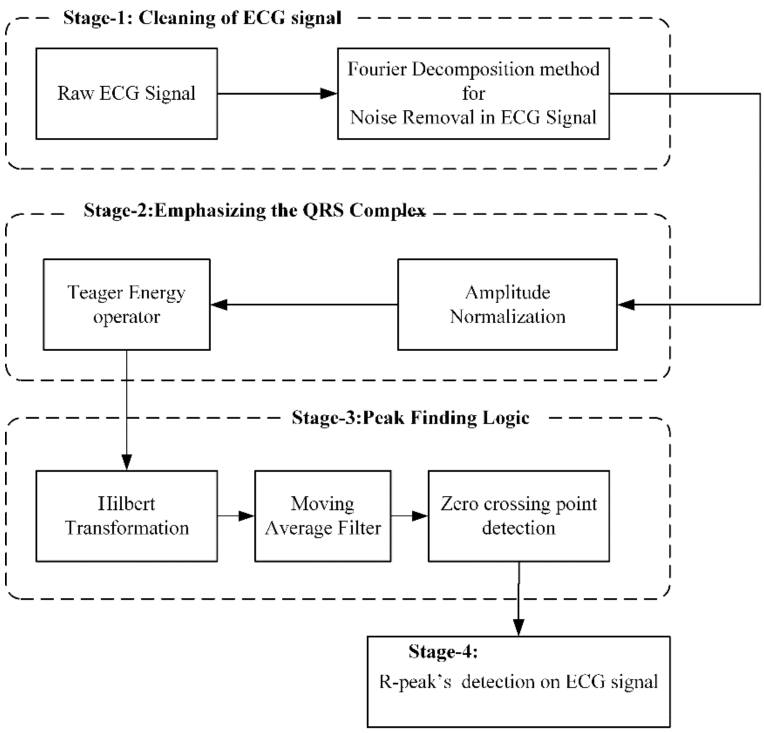

Figure 1. Block diagram of improved R-peak marking method

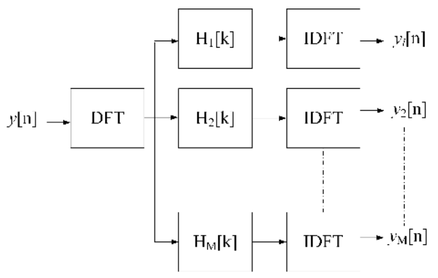

Figure 2. Block diagram of Frequency Decomposition Method

The Discrete Fourier Transform (DFT) based zero-phase filter bank is used for implementing the FDM. The block diagram of the FDM technique using Zero phase filtering is described in Figure 2.

The given ECG signal y[n] is break down into a set of orthogonal frequency bands using the following signal decomposition

$$y[n] = b_0 + \sum_{i=1}^{M} y_i[n] \tag{1}$$

Here b_0 is average value of the Signal *y[n]*, and {y_1[n], y_2[n], y_3[n], … y_k[n]} are Fourier intrinsic band functions. Consider frequency below 0.7 Hz as baseline wander frequency and 50 Hz and above as powerline interference. The frequency response of i^{th} band in the filter-bank can be obtained by defining $H_i[k] = 1$ for the required band of frequencies and zero for the range of noise frequencies (below 0.7 Hz and above 50Hz). Mathematically the filter bank can be defined as

$$\left.\begin{aligned} H_i[k] &= 0, \quad (k_{i-1}+1) \le k \le (N-k_i) \\ &= 0, \quad (N-k_i) \le k \le N-k_{i-1}-1 \\ &= 1, \quad \text{otherwise} \end{aligned}\right\} \tag{2}$$

where, *i* is 1, 2…M using inverse discrete Fourier transform (IDFT) operation, the signal components $y_i[n]$ are obtained as

$$y_i[n] = \sum_{k=0}^{N-1}\left[H_i[k]Y[k]\exp\left(\frac{j2\pi kn}{N}\right)\right] \tag{3}$$

where, Y[k] is discrete Fourier transform of y[n].

The proposed zero phase filter bank preserve the significant features like positions of all peaks. So that we can extract meaningful information from filtered ECG signal. However, the computational complexity also reduced by implementing the required DFT and IDFT using fast Fourier transform (FFT) algorithm. Figure 3 illustrate the performance of FDM for Denoising the ECG signal. Figure 3 (a) depicts the Original ECG signal y[n], Figure 3 (b) shows the 0.2Hz frequency noise which resembles the BW, Figure 3 (c) illustrate the 50Hz frequency noise which resembles the PLI, Figure 3 (d) shows the noise contaminated signal generated by adding all the above three signal. The filtered ECG signal is shown in Figure 3 (e) after applying FDM.

3.2 Amplitude normalization and Teager energy signal generation

This is the second step of the proposed method to identify R-peak. In this step, we implemented both amplitude normalization and generation of TEO signal for emphasizing the QRS complexes in the ECG signal. Normalization of the signal is useful for better discrimination of positive peaks and negative peaks. By doing this we can limit the signal amplitude to [-1, 1]. We normalize the signal y (n) by

$$\check{y}(n) = \frac{y(n)}{\max_{n-1}^{N}(|y[n]|)} \tag{4}$$

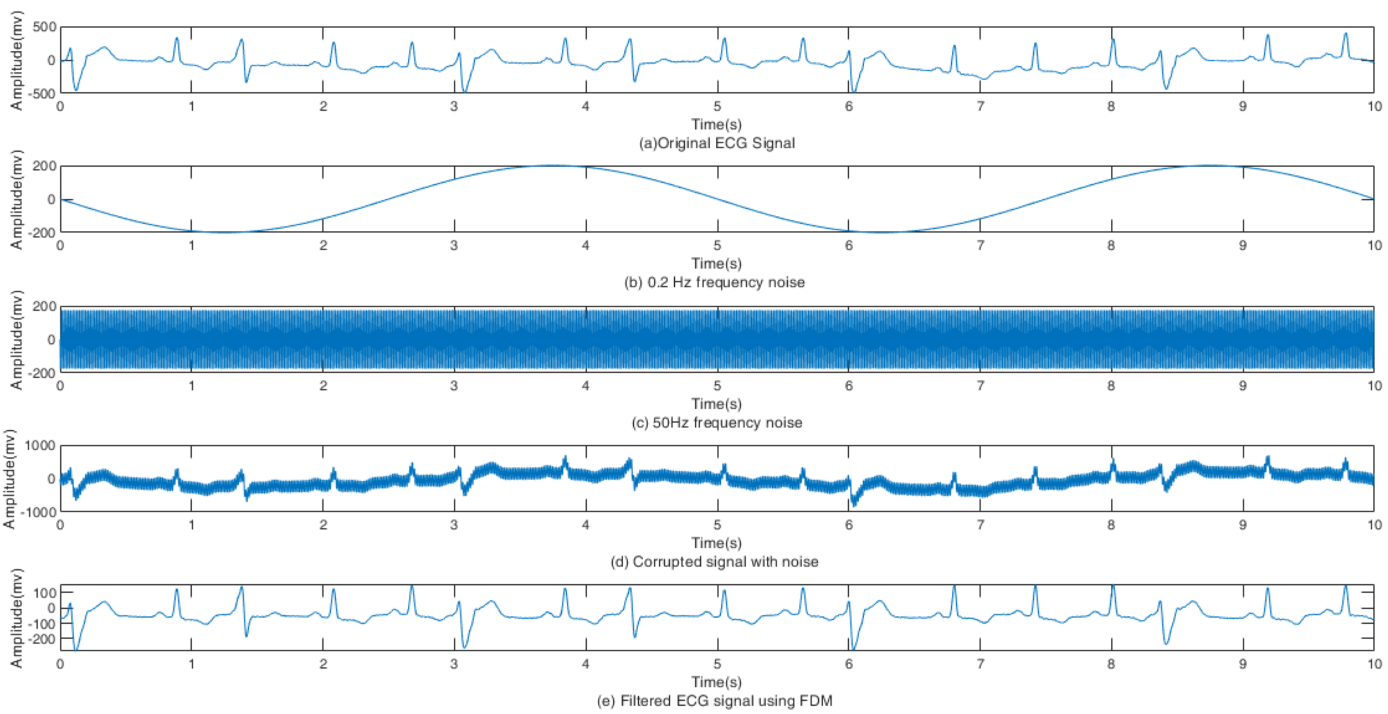

Figure 3. Illustration of denoising ECG signal

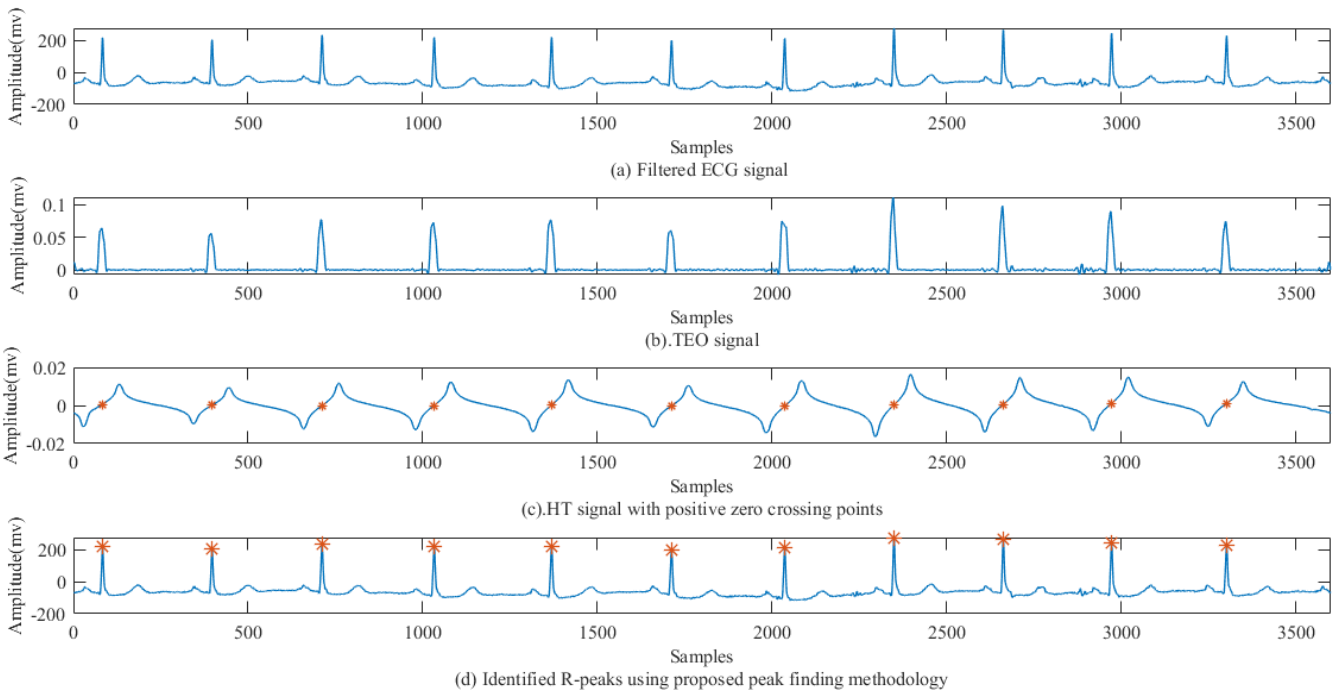

Figure 4. Identifying R-peaks using proposed method

where, each sample of y (n) is divided by maximum value of the signal. Amplitude normalization improves the detection of negative R-peaks. The primary purpose of generating TEO signal is to boost the original amplitudes of R-peaks. It was originally created by Kaiser [21]. TEO for a signal $\check{y}(n)$ in its discrete form can be generated by using following equation:

$$\Psi_y[n] = \check{y}(n)^2 - \check{y}(n-1) * \check{y}(n+1) \quad (5)$$

The TEO has been commonly used as a peak detector in many applications. Using TEO, it is possible to reduce the effect of P and T waves for reliable identification of R-peaks.

3.3 Accurate R-peak detection

From many years, the position of R-peaks is detecting by comparing the amplitude of the signal with the predefined threshold values. The secondary threshold value and search back methods are also exploited for reduction of errors. Nevertheless, in the case of diseased patient with varying wave function characteristics the search back mechanism with the second threshold value also does not give efficient results. In this work, HT and ZCD are used to construct a novel automatic R-peaks finding technique. The Figure 4 depicts how the HT signal identifies the R-peaks by marking its zero crossing points using Zero Cross Detector. This eliminates the complexity of comparison with various threshold values.

The HT of given signal z (t) is defined as

$$\tilde{z}(t) = H[z(t)] = \frac{1}{\pi t} * z(t) = \frac{1}{\pi} \int_{-\alpha}^{\alpha} \frac{z(\tau)}{t-\tau} d\tau \quad (6)$$

The process of finding R-peaks is depicted in Figure 4. Filtered ECG signal is shown in the Figure 4 (a). How the QRS complexes are enhanced in generated TEO signal is depicted in Figure 4 (b). Figure 4 (c) Illustrating the positive zero crossing points in the HT signal. Figure 4 (c) shows the identified R-peaks on the given ECG signal. Locating R-Peaks is difficult in the case of fragmented QRS complexes and low-frequency drift in the signal. To overcome this HT signal is passed through the Moving Average filter. The location of positive zero crossing points on the HT signal represents the R-peaks. which can resemble the positions of R-Peaks. By projecting these locations on the ECG signal, we can find the R-Peaks with ± 20 samples. By searching the point which is more away from the zero-dc line in the searching window of ±20 samples of the identified R-peak locations in the previous test we can find the original R-peak locations.

4. RESULTS

The proposed work is evaluated using the well-known Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database [30]. This repository contains 48 ECG recordings, which are sampled at a rate of 360 Hz. The quality of these records is acceptable for performing the performance evaluation of proposed method. It was implemented on MATLAB 2018a. To validate the proposed work, we considered different performance metrics. Which are percentage of sensitivity (Se), percentage of positive predictivity (+P), percentage of detection error rate (DER) and percentage of accuracy (ACC) are chosen. The performance metrics are calculating using the following equations.

$$Se(\%) = \frac{TP}{TP + FN} X\ 100\%$$

$$+P(\ \%) = \frac{TP}{TP + FP} X\ 100\%$$

$$DER(\%) = \frac{FP + FN}{TP} X100\%$$

$$ACC(\%) = \frac{TP}{TP + FP + FN} X\ 100\ \%$$

Here the true positive (TP) represents the exact identification of R-peaks, false positive (FP) represents the number of false identified R-peaks, false negative (FN) represents the number of missing R-peaks. The experimental results for illustrating the efficiency of the proposed method are summarized in Table 1. The observed error rate of 0.19%, which is optimum among the methodologies taken from the proven literature. The records which are having baseline below the origin are giving more error rate. Record 232 has a number of long pauses, although our method performed well as shown in the Figure 5. The ECG record 232 is depicted in Figure 5 (a). Filtered ECG record 232 is shown in Figure 5 (b). TEO signal generated is depicted in Figure 5 (c). Figure 5(d) Illustrating the positive zero crossing points on HT signal. The Identified R-peaks on record-232 is shown in Figure 5 (e).

It was observed that an accuracy of 99.97%, the sensitivity of 99.98% and positive prediction of 99.98% is achieved with the proposed method. The efficiency of the given R-peaks finding technique is compared with other exiting methodologies and summarized in Table 2. It shows the significant improvement compared with the techniques which use the non-linear filtering in their preprocessing stage [15-18]. and comparable results with the Fractional Fourier transform [14], S-transform [19], and wavelet transforms [20]. The proposed methodology works well in the presence of high frequency PLI and low frequency BW without affecting other features of the ECG signal.

Table 1. Performance evaluation of the proposed R-peak finding method using MIT-BIH arrhythmia database

Record No.	Total (beats)	TP (beats)	FN (beats)	FP (beats)	DER (%)	Se (%)	+P (%)	Accuracy (%)
100	2273	2273	0	0	0.00	100	100	100
101	1865	1864	1	0	0.05	99.95	100	99.95
102	2187	2187	0	0	0.00	100	100	100
103	2084	2084	0	0	0.00	100	100	100
104	2229	2229	0	0	0.00	100	100	100
105	2572	2571	1	0	0.04	99.96	100	99.96
106	2027	2027	0	1	0.05	100	99.95	99.95
107	2137	2137	0	0	0.00	100	100	100
108	1763	1761	2	1	0.17	99.89	99.94	99.83
109	2532	2532	0	0	0.00	100	100	100
111	2124	2124	0	0	0.00	100	100	100
112	2539	2539	0	0	0.00	100	100	100
113	1795	1795	0	0	0.00	100	100	100
114	1879	1879	0	0	0.00	100	100	100
115	1953	1952	1	1	0.10	99.95	99.95	99.90
116	2412	2409	3	1	0.17	99.88	99.96	99.83
117	1535	1535	0	0	0.00	100	100	100
118	2278	2278	0	1	0.04	100	99.96	99.96
119	1987	1987	0	0	0.00	100	100	100
121	1863	1863	0	0	0.00	100	100	100
122	2476	2476	0	0	0.00	100	100	100
123	1518	1518	0	0	0.00	100	100	100
124	1619	1619	0	0	0.00	100	100	100
200	2601	2601	0	0	0.00	100	100	100
201	1963	1963	0	0	0.00	100	100	100
202	2136	2136	0	0	0.00	100	100	100
203	2980	2978	2	0	0.07	99.9	100	99.93
205	2656	2656	0	0	0.00	100	100	100
207	1862	1862	0	0	0.00	100	100	100
208	2955	2951	0	2	0.07	100	99.93	99.93
209	3005	3005	0	0	0.00	100	100	100
210	2650	2648	2	0	0.08	99.92	100	99.92
212	2748	2744	0	0	0.00	100	100	100
213	3251	3251	0	0	0.00	100	100	100
214	2262	2261	1	1	0.09	99.96	99.96	99.91
215	3363	3363	0	0	0.00	100	100	100
217	2208	2207	1	0	0.05	99.95	100	99.95
219	2154	2154	0	0	0.00	100	100	100
220	2048	2048	0	0	0.00	100	100	100
221	2427	2427	0	0	0.00	100	100	100
222	2483	2483	0	0	0.00	100	100	100
223	2605	2604	1	0	0.04	99.96	100	99.96
228	2053	2051	2	0	0.10	99.90	100	99.90
230	2256	2256	0	0	0.00	100	100	100
231	1571	1569	2	0	0.13	99.87	100	99.87
232	1780	1780	0	3	1.011	100	98.99	98.99
233	3079	3077	2	0	0.06	99.94	100	99.94
234	2753	2753	0	0	0.00	100	100	100
Total	1,09,496	109467	21	11	0.19	99.98	99.98	99.97

Table 2. Comparison of R-peak identification methods

Ref.	Methodology			FP (beats)	FN (beats)	Se (%)	+P (%)	Acc (%)
	Preprocessing Stage	Improving the QRS Complex	Peaks identification method					
[14]	Median filter and SG smoothing filtering	RMS value of third power of ECG	Threshold based Peak detection	428	509	99.50	99.56	99.08
[15]	Filtering with LPF and HPF	Teager Energy Operator	Threshold based Peak detection	33	285	99.74	99.97	99.71
[16]	Digital FIR Filtering	Squaring, MA Filter and Normalization	Adaptive Threshold Operation	182	184	99.83	99.83	99.66
[17]	Shift Invariant Wavelet Transform (ShIWT)	Nonlinear Energy Operator (NEO)	Simple Thresholding Operation	254	264	99.75	99.76	99.52
[18]	Fractional Fourier Transform	Fractional Stock well Shannon energy (FrSS)	Threshold based on the FrSS envelope and search back method	67	46	99.95	99.93	99.89
[19]	Discrete Wavelet Transform	Modified Shannon Energy Envelope	Peak Energy determination	99	79	99.93	99.91	99.83
[20]	S-Transform	Shannon Energy Envelope	Threshold based Peak detection	97	171	99.84	99.81	99.66
Proposed Method	Fourier decomposition method	Teager Energy operator	Hilbert Transform and positive zero cross point detection technique	11	21	99.98	99.98	99.97

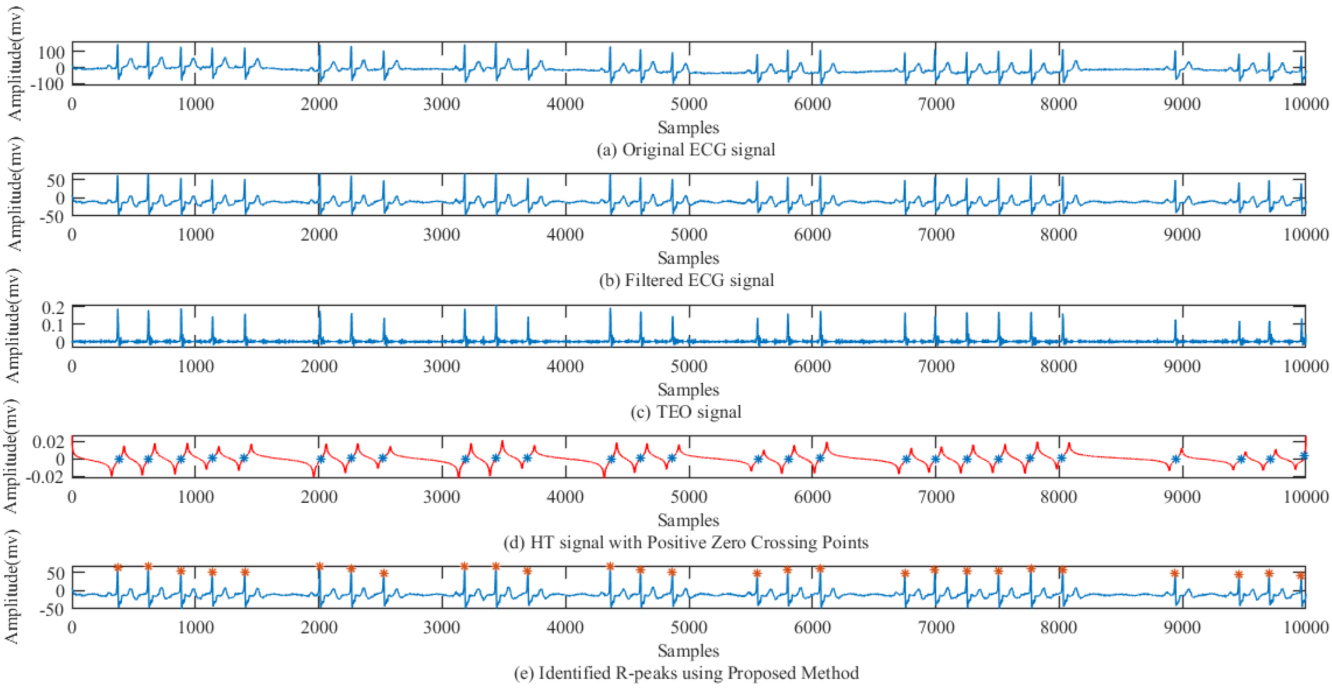

Figure 5. Illustration of R-peaks identified on record-232 using proposed method

5. CONCLUSION

An improved peak finding methodology for the reliable detection of R-peaks described in four stages, which exploits the advantages of Fourier decomposition, Teager Energy Operator and Hilbert Transform. The preprocessor is implemented based on Fourier decomposition method using Zero phase filter bank which can eliminate the PLI and BW more efficiently without affecting required peak positions and other features of the signal. The QRS complexes are improved by TEO that significantly increases the accuracy of R-peaks detection. The HT and positive ZCD are used for identification of R-peaks. Comparison of amplitude thresholds is not required in this approach. The experimental results are presented and compared with the existing studies. The standard MIT-BIH database is used for evaluating the effectiveness of the proposed method. The proposed methodology improved the results and achieved accuracy of 99.97%, sensitivity of 99.98% and positive predictivity of 99.98%. From Table 2, it is observed that the proposed method gives a higher accuracy as compare to the existing methods.

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