Biomedical Engineering Letters (2019) 9:145–151
https://doi.org/10.1007/s13534-018-0087-y

ORIGINAL ARTICLE

Efficient QRS complex detection algorithm based on Fast Fourier Transform

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Received: 25 June 2018 / Revised: 10 September 2018 / Accepted: 11 October 2018 / Published online: 25 October 2018

Abstract

An ECG signal, generally filled with noise, when de-noised, enables a physician to effectively determine and predict the condition and health of the heart. This paper aims to address the issue of denoising a noisy ECG signal using the Fast Fourier Transform based bandpass filter. Multi-stage adaptive peak detection is then applied to identify the R-peak in the QRS complex of the ECG signal. The result of test simulations using the MIT/BIH Arrhythmia database shows high sensitivity and positive predictivity (P_P) of 99.98 and 99.96% respectively, confirming the accuracy and reliability of proposed algorithm for detecting R-peaks in the ECG signal.

Keywords Electrocardiogram (ECG) · Cardiovascular diseases (CVD) · Fast Fourier Transform (FFT)

1 Introduction

At present, medical research organizations mainly focus on cardiovascular diseases (CVD) and related problems due to increased mortality worldwide from CVDs. Further, technological progress in cardiac function assessments has become the nucleus and heart of all leading research studies in the area of CVDs [1]. Use of technologies in hospitals and medical facilities has undergone stupendous advancements thereby changing the face of the traditional and regular cardiovascular-diagnosis. Amongst the commonly used clinical cardiac tests, electrocardiogram (ECG) analysis which represents the electrical activity of the heart is utilized to test the heart-related irregularity [2]. ECG signals are captured from the polarization and depolarization of the ventricles and atrias, that alternately contract and expand to pump blood throughout the body [3]. This polarization and depolarization of the chambers produce the ECG signal."

The ECG signals demonstrate the latent operation of the heart and constitute events that concur and coexist with the succession of depolarization and repolarization of the atria and ventricles. Figure 1 represents the different ECG waves produced during a cardiac cycle. The QRS complex is made-up of two troughs, namely, 'Q' and 'S' and a sharp R-peak. The literature identifies a higher detection accuracy of these three events (P-peak, QRS complex and T-peak) during the analysis period of fewer than 30 min.

Also, to ameliorate the advancement in the technological diagnostic tool, long duration monitoring of ECG signals is conducted by connecting the electrodes of ECG recorder to a device that banks on the wireless transmission, considered as a fundamental requirement for early detection of CVDs [4]. A precise, exact and coherent e-health device, supplementing CVD screening and diagnosis process, with an efficient well-ordered ECG system is the need of the hour. The technique should be cost-effective, authentic, expandable and capable of effectual patient tracking with a medical data management tool. Such a tool becomes a necessity for tracking the health of many CVD patients to prevent critical heart failure and to provide rapid medical attention to patients. A model of a wearable ECG monitoring system that can be used for the acquisition,

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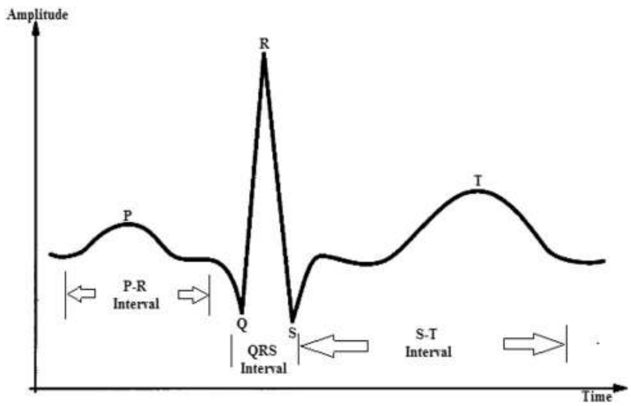

Fig. 1 ECG signal

processing and wireless transmission of ECG data for monitoring the health of CVD patient is shown in Fig. 2.

Wireless transmission of the ECG data is the major source of power consumption in the ECG monitoring system. Hence, a solution that reduces the size and protects the integrity of the signal quality is required. Size of the transmitted ECG data can be reduced using an efficient compression method. However, most of the high-performance compression methods are complex and require high energy consumption, rendering them unsuitable for wearable ECG monitoring systems [5–7]. Therefore, an efficient compression method that is simple, fast and suitable for a large duration of ECG data must be identified.

The present work outlines a simple, fast, and efficient R-peak detection algorithm that holds the integrity of the signal. Optimal results are obtained by considering hardware complexity and detection accuracy as performance metrics for the proposed R-peak detection algorithm. An FFT (Fast Fourier Transform) based bandpass filter is employed to accurately isolate the ECG data from the recorded which may contain noise. Adaptive peak detection is then used to identify the R-peak in the QRS complex of the ECG signal. Simulation results verify the effectiveness of the proposed R-peak detection algorithm.

2 Proposed ECG detection scheme

2.1 Database

There are various standard databases which provide ECG waveform namely, AHA database, PTB diagnostic ECG database, MIT-BIH arrhythmia database. The MIT-BIH Arrhythmia database (MITADB) from *physionet.org* [8] is utilized in the proposed algorithm. It provides around thirty-four different ECG samples out of which some contain large amounts of noise. The data can be of different duration ranging from 10 s to 30 min and 05.556 s.

2.2 Proposed algorithm description

As the ECG signal is an electrical signal and is vulnerable to various forms of noise, namely, power line interference, electromyographic noise (EMG), baseline drift, and a composite noise constructed from the noises that are

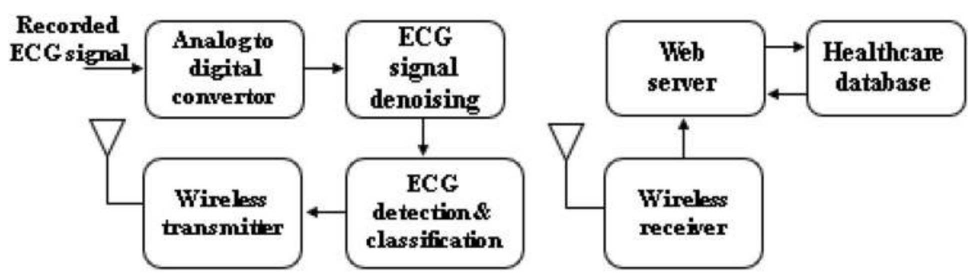

Fig. 2 Wearable ECG monitoring system Model

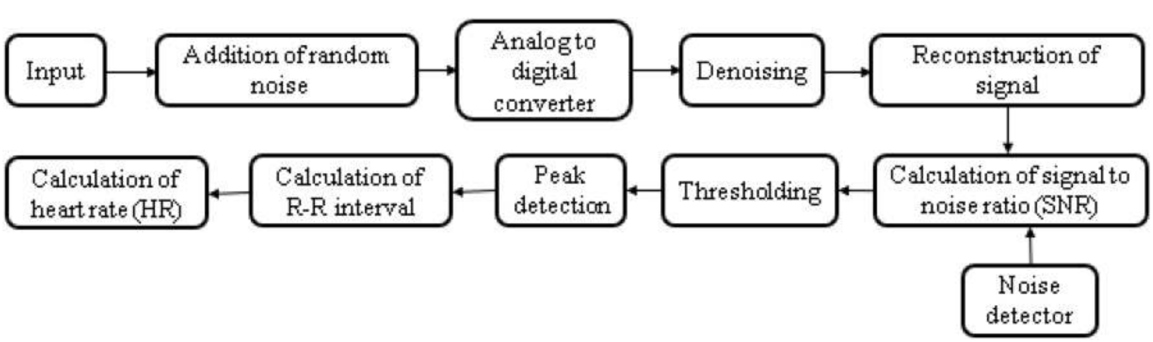

Fig. 3 Block diagram representation of the proposed FFT based ECG denoising and adaptive R-peak detection algorithm

present in the atmosphere/surroundings [9]. Various de-noising techniques namely, time-domain [10], time–frequency domain (wavelet transform) [11–17], digital filtering [18–20], and Fourier transform to name a few, are proposed in the last few decades. An FFT based filtering and adaptive R-peak detection algorithm are selected based on the trade-off between algorithmic complexity, robustness and detection performance. Initially, to reduce noise, the ECG signal is isolated from the other signals using a bandpass filter implemented using the FFT. Then, the R-peaks are identified by implementing an adaptive peak detection algorithm. Using a fixed time duration modeled from a single ideal ECG cycle, false R-peak detections are identified. The block diagram representation of the proposed FFT based denoising and adaptive R-peak detection algorithm is shown in Fig. 3.

The pseudo code of the proposed algorithm is as follows:

different methods such as moving average [21], adaptive filtering [22], wavelet transform [23], to name the important. In this work, Fast Fourier Transform is utilized to implement a bandpass filter with cut-in and cut-off frequencies 0.5 Hz and 15 Hz respectively to reduce the various noises present in the ECG signal. The noise is reduced by multiplying a shifted rectangle function defined by Eq. (1) with the Fourier spectrum of the ECG signal using Eq. (2).

$$w_r[k] = \left\{ \begin{array}{ll} 1, & -\frac{M-1}{2} \leq k \leq \frac{M-1}{2} \\ 0, & otherwise \end{array} \right\} \quad (1)$$

$$Y[k] = w_r[k - C_0]X[k] \quad (2)$$

where M is the width of the basdpass filter equal to 15.5 Hz, C_0 is the centre frequency of the bandpass filter equal to 7.75 Hz, k represents frequency, and $X[k]$ is the Fourier spectrum of the input ECG signal.

```
START program
LOAD ECG data in Inp_n
IF input signal is inverted THEN
   INVERT and STORE Inp_n IN Inp_n
ENDIF
COMPUTE and STORE FFT of input IN Inp_FFT
FOR frequency f_k IN RANGE {0 TO maximum frequency in Inp_FFT}
   IF frequency f_k less than 0.5Hz OR frequency f_k more than 15Hz THEN
      SET amplitude of Inp_FFT at frequency f_k TO 0
   ENDIF
ENDFOR
COMPUTE and STORE inverse FFT of Inp_FFT IN Out_n
COMPUTE and STORE magnitude of highest peak of Out_n IN P_max
COMPUTE and STORE 10% of P_max IN Pass_mark_1
FIND and STORE peaks with amplitude more than Pass_mark_1 IN Pass_1_peaks
COMPUTE and STORE mean of Pass_1_peaks IN P_mean
COMPUTE and STORE 45% of P_mean IN Pass_mark_2
FIND and STORE peaks with amplitude more than Pass_mark_2 IN Pass_2_peaks
PLOT Pass_2_peaks
END program
```

Various low frequency noise, namely, baseline wandering and high frequency noises, namely, additive white gaussian noise, muscle contraction (EMG), power line interference affects an ECG signal while recording. The MITADB contains ECG signals with high and low noise levels. Also, some random noise sources are generated and added to the original ECG signal to test the algorithm for critical cases. The analog input ECG signal is first sampled at 360 Hz to convert the data into a digital format which can be analyzed and processed further. The sampled data is directly taken from the MITADB. The noise, as described above, in the recorded ECG signal can be reduced using

The final de-noised ECG signal can then be obtained by applying the inverse FFT on the processed frequency data Eq. (3).

$$y[n] = \frac{1}{L}\sum_{k=0}^{L-1} w_r[k - C_0]X[k]W_L^{-kn} \quad (3)$$

The FFT and inverse FFT are calculated using Eqs. (4) and (5), where $x[n]$ and $X[k]$ are the input signal and FFT of the input signal, respectively, k represents frequency, n represents sample, L is the length if $x[n]$, and W_L is given by Eq. (6).

$$X[k] = \sum_{n=0}^{L-1} x[n] W_L^{kn}, \quad 0 \le k \le L-1 \tag{4}$$

$$x[n] = \frac{1}{L} \sum_{k=0}^{L-1} X[k] W_L^{-kn}, \quad 0 \le n \le L-1 \tag{5}$$

$$W_L = e^{-j\frac{2\pi}{L}} \tag{6}$$

The de-noised ECG signal is compared with the original ECG signal with the help of a noise detector to test the removal of noise sources. The signal to noise ratio (SNR) of the proposed de-noised algorithm is calculated using Eq. (7).

$$SNR = 10 \log_{10}\left(\frac{\sum_i s_i}{\sum_i |s_i - \hat{s}_i|^2}\right) \tag{7}$$

where S_i, $\hat{S}_i$ are the original signal and reconstructed signal, respectively. If the noise detector identifies any noise in the de-noised ECG signal, then the whole denoising process is repeated. When the noise in the recorded signal is reduced to a minimum level, the R-peaks are identified through a multistage adaptive peak detection process. The first stage of the peak detection process identifies the highest peak and stores 10% of this peak as the stage one mark. The second and final stage mark is obtained by taking 45% of the mean of all R-peaks found using the stage one mark. This method of multistage adaptive peak detection allows the algorithm to partially adapt to different signals compared to a fixed threshold value. After the R-peak detection, the interval between two consecutive R-peaks are determined by taking the ratio of the distance between two adjacent R-peaks and the frequency of the original signal. Then, the heart rate (HR) of the signal is calculated using Eq. (8).

$$\text{Heart Rate (HR)} = \left(\frac{60}{\text{Average R} - \text{R peak interval}}\right) \tag{8}$$

The heart rate is used to analyze the physiological condition of the person. If the heart rate exceeds 100 bpm continuously, then the subject is diagnosed with sinus tachycardia, and if the heart rate is below 50 bpm continuously, then the diagnosis is sinus bradycardia.

3 Result and discussion

Sensitivity, positive predictability (P_p) and detection error-rate (D_{ER}) are the performance measure used to calculate the performance of the proposed R-peak detection algorithm. The Sensitivity, P_P, and D_{ER} are computed using Eqs. (9–11).

$$Sensitivity = \frac{T_P}{(T_P + F_N)} \tag{9}$$

$$P_P = \frac{T_P}{(T_P + F_P)} \tag{10}$$

$$D_{ER} = \left(\frac{F_P + F_N}{Total\ number\ of\ peaks}\right) \tag{11}$$

where true positive (T_P) is the count of R-peaks detected as R-peaks, false negative (F_N) is the count of missed R-peaks, and false positive (F_P) is the count of extra detected R-peaks. Sensitivity provides the information about the percentage of truly detected peaks out of the total true peaks. P_P gives information on the percentage of detected true peaks out of all detected peaks. The proposed technique is performed using the MITADB [24] with 10-second ECG signal and full-length ECG signal data. The R-peak detection results for the ten-seconds ECG signals taken from the MITADB is reported in Table 1. Sensitivity, P_P, D_{ER} and R–R peak time and HR are considered to evaluate the small ECG data set.

Table 2 concludes that the proposed detector achieves the highest sensitivity and P_P of 99.65 and 99.65% respectively using the MITADB of small-length. The proposed detector obtained the highest sensitivity and P_P of 100% with 108.mat and 214.mat signals from the MITADB which contain maximum noise [25].

The R-peak detection results for the full-length ECG signals taken from the MITADB is listed in Table 3. It is noticed from Table 4, that the proposed detector achieves the highest sensitivity and P_P of 99.98% and 99.96 respectively using the MITADB of full-length.

The performance of the proposed R-peak detector under noisy conditions are shown in Fig. 4. Through the implementation of the FFT based bandpass filter (Fig. 4a bottom and top right plots), most of the noise in the recorded ECG signal (Fig. 4a top left plot) is removed (Fig. 4a bottom left plot). The de-noised result (Fig. 4b) is then processed using an adaptive two-stage R-peak detection method. The first stage (Fig. 4c) uses the highest peak in the signal as a basis for detecting potential R-peaks. The second and final stage of this process generates a new limit using the R-peaks detected by the first stage, to identify the R-peaks more accurately. Each stage further utilizes a time duration based upon a single ideal ECG cycle to analyze the R-peak distribution and eliminate false detections. This two-stage process can further be expanded to an *N* stage process that can potentially result in more refined results. However, each additional stage increases the computational complexity and time required to obtain results. Hence restricting the process to two stages achieves a balance between complexity and detection accuracy, this allows the proposed algorithm to be unique and efficient.

Table 1 Peak detection results of the proposed design using ten-seconds ECG data

Signal	100	101	102	103	104	105	106	107	108	109	111	112	113	114	115	116	117
SE (%)	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
+ P (%)	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
DER (%)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R–R time	0.8	0.89	0.82	0.85	0.81	0.72	0.99	0.85	0.97	0.64	0.85	0.69	1.07	1.13	1	0.75	1.16
HR	75	67.4	73.2	70.6	74.1	83.3	60.6	70.6	61.9	93.8	70.6	87	56.1	53.1	60	80	51.7
Signal	118	119	121	122	123	124	200	201	202	205	207	208	209	210	212	213	214
SE (%)	100	100	100	100	100	100	93.3	100	100	100	90	100	100	100	100	100	100
+P (%)	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
DER (%)	0	0	0	0	0	0	0.66	0	0	0	0.1	0	0	0	0	0	0
R–R time	0.83	0.92	0.99	0.66	1.26	1.21	1.13	0.7	1.12	0.66	1.21	1.09	0.63	0.67	0.66	0.54	0.8
HR	72.3	65.2	60.6	90.9	47.6	49.6	53.1	85.7	53.6	90.9	49.6	55	95.2	89.6	90.9	111	75
Signal	215	217	219	220	221	222	223	228	230	231	232	233	234				
SE (%)	100	100	100	100	100	100	100	100	100	100	100	100	100				
+ P (%)	100	100	100	100	100	100	93.3	100	92.9	100	100	100	100				
DER (%)	0	0	0	0	0	0	0.66	0	0.07	0	0	0	0				
R–R time	0.53	0.84	0.73	0.83	0.83	0.79	0.75	0.82	0.73	1	1.02	0.69	0.66				
HR	113	71.4	82.2	72.3	72.3	75.9	80	73.2	82.2	60	58.8	87	90.9				

Table 2 Total performance of the proposed design using short-length ECG data

Signal	SE (%)	+ P (%)	DER (%)	R–R time	HR
Average	99.65	99.65	0.6	0.86	73.28

Table 4 Total performance of the proposed design using full-length ECG data

Signal	SE (%)	+P (%)	DER (%)	R–R time	HR
Average	99.98	99.96	0.03	0.91	67.99

Table 3 Peak detection results of the proposed design using full-length ECG data

Signal	100	101	102	103	104	105	107	108	109	111	112
SE (%)	100	100	100	100	100	99.92	100	99.65	100	100	100
+ P (%)	100	100	100	100	99.95	99.96	100	99.88	100	100	100
DER (%)	0	0	0	0	0.0004	0.001	0	0.004	0	0	0
R–R time	0.8	0.97	0.82	0.86	0.83	0.72	0.86	1.11	0.73	0.86	0.71
HR	75	67.81	73.17	69.76	72.28	83.33	69.76	79.91	52.9	69.76	84.5
Signal	114	115	116	117	118	119	121	122	123	124	201
SE (%)	99.89	100	100	100	100	100	100	100	100	100	100
+P (%)	99.94	100	100	100	100	100	100	100	100	100	99.54
DER (%)	0.001	0	0	0	0	0	0	0	0	0	0.0005
R–R time	0.96	0.92	0.75	1.17	0.83	0.9	0.97	0.72	1.19	1.14	1.01
HR	62.5	65.21	80	51.28	72.28	66.66	61.85	83.33	50.42	52.63	59.4

3.1 Comparison with the existing methods

Comparison of the proposed algorithm with the existing algorithms confirms that the proposed algorithm has better detection accuracy regarding Sensitivity, P_P, and D_{ER}. The proposed R-Peak detector achieves the highest sensitivity and positive predictability of 99.98 and 99.96%, respectively using the MITADB of full-length (Fig. 5). There are few other algorithms such as genetic algorithm and a neural network which offer good performance, but their

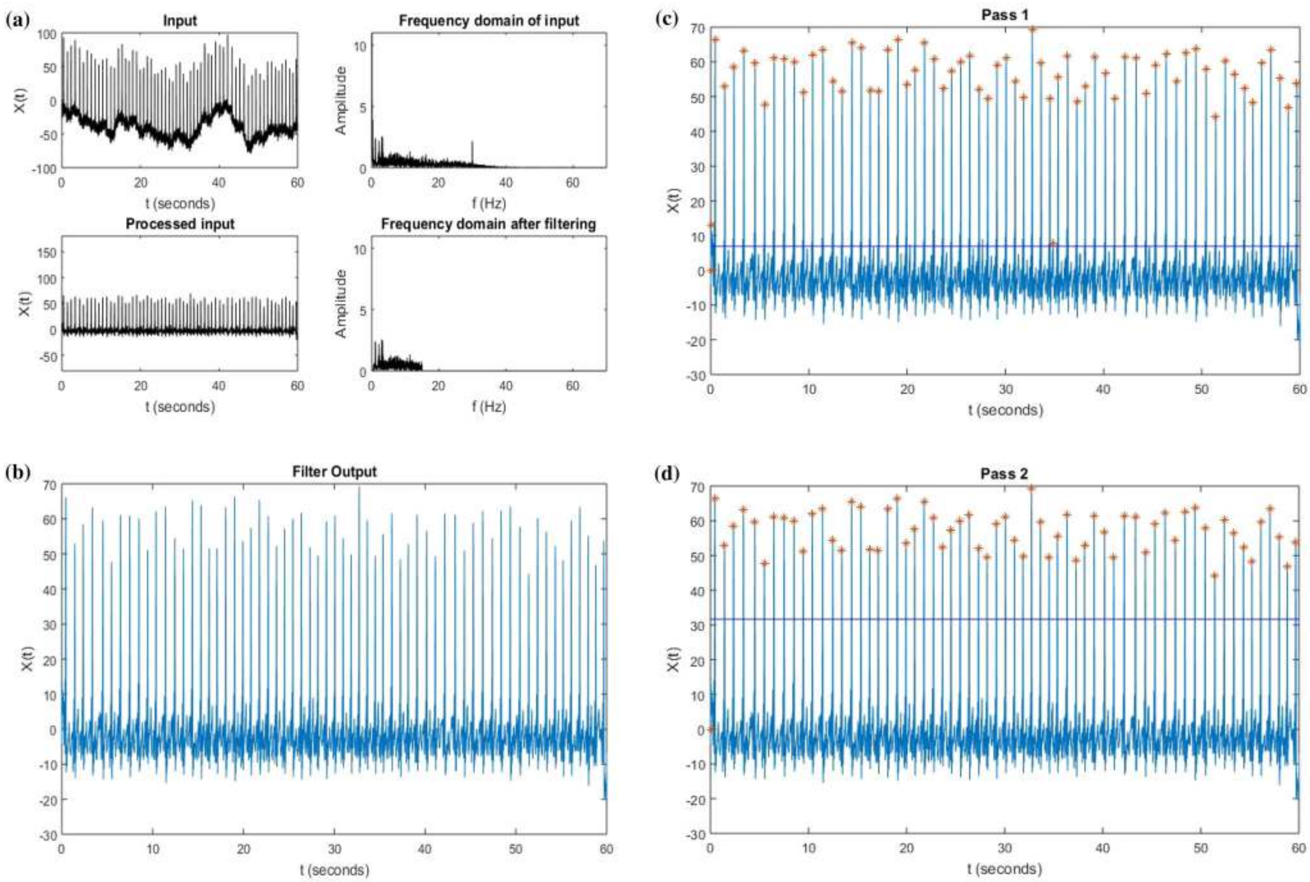

Fig. 4 The output of the proposed algorithm. *Note*: The 115.*mat* input ECG signal taken from the MITADB is represented in **a**, with the de-noising process shown using 4 subplots. **b** The output of the FFT based bandpass filter. **c** The result of the first pass in the R-peak detection process with the stage 1 mark (horizontal navy-blue line) and the detected peaks (orange asterisks). **d** The result of the final stage with the stage 2-mark horizontal navy-blue line) and the detected peaks (orange asterisks). (Color figure online)

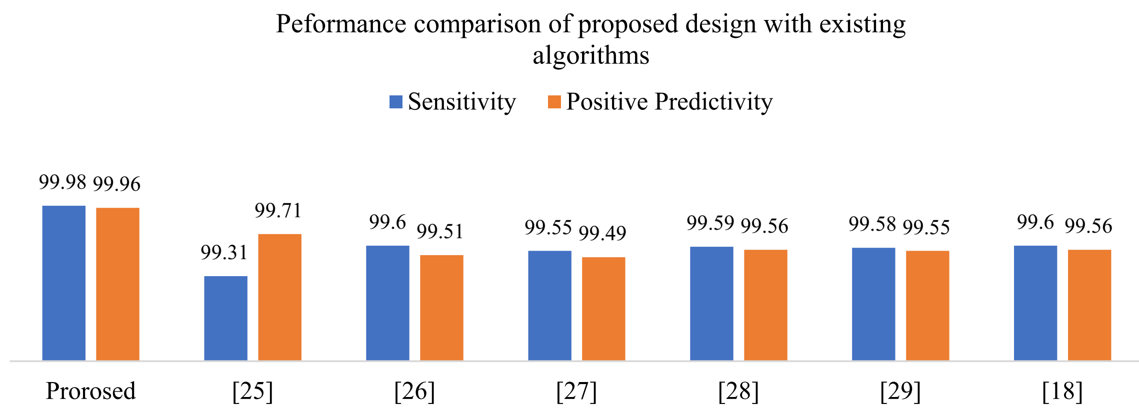

Fig. 5 Performance comparison of the proposed algorithm with the existing R-peak detection algorithms

computational complexities are relatively high compared to the proposed FFT algorithm. The proposed FFT algorithm is simple, cheaper and requires less hardware when compared to the existing techniques. Hence, the proposed algorithm is better suited for R-peak detection.

4 Conclusion

In this paper, an attempt to remove the noise from an ECG signal is addressed through the use of an efficient FFT based denoising algorithm. The usage of adaptive peak detection technique along with FFT improved the detection accuracy of the R-peak, which is used to calculate the heart rate. The proposed algorithm achieves a sensitivity rate and P_P of 99.65% with a D_{ER} of 0.6% for short-length ECG data. With the full-length ECG data, it achieves a sensitivity rate of 99.98% and P_P of 99.96% with a D_{ER} of 0.03%. The results of the comparison with other ECG de-noising and detection algorithms shows an impressive 99.65% (sensitivity) and 99.65% (P_P), confirming the accuracy and reliability of the proposed algorithm. The use of FFT to de-noise the ECG signal makes the proposed algorithm simple and efficient, allowing this approach of de-noising and detection to be made available to wearable devices such as pacemakers and portable ECG monitoring stations to record, collect and transmit data to a common server and take immediate medical action.

Compliance with ethical standards

Conflict of interest Authors Ashish Kumar, Rama Komaragiri and Manjeet Kumar declares that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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