Journal of Ambient Intelligence and Humanized Computing (2022) 13:961–972
https://doi.org/10.1007/s12652-021-03484-3

ORIGINAL RESEARCH

Detection of R-peaks using fractional Fourier transform and principal component analysis

Varun Gupta[1] · Monika Mittal[2] · Vikas Mittal[3] · Yatender Chaturvedi[4]

Received: 20 October 2020 / Accepted: 31 August 2021 / Published online: 13 September 2021

Abstract
An electrocardiogram (ECG) is world's most recognized, widely accepted and essential primitive diagnostic tool to assess health status of heart of a subject (patient) by analyzing its constituent P, QRS and T waves. QRS wave is further consists of three waves namely; Q-wave, R-wave, and S-wave, where R-wave has highest amplitude (about 1 mVolt known as R-peaks). Despite of higher amplitudes, their detection by visual inspection is still challenging due to physiological variability and presence of various types of noise/distortion in acquired ECG signal. Pre-processing of raw ECG datasets can help in tackling these two problems to some extent but that incurs an appreciable amount of computational effort. Therefore in this paper, the need of pre-processing is made redundant by using fractional Fourier transform (FrFT) for extracting features i.e. directly using the raw ECG datasets alongwith using well-known principal component analysis (PCA) for detecting R-peaks effectively in the presence of varying morphologies of ECG signal and various types of noise/distortions. Obviating the need of pre-processing altogether results in faster computations and use of PCA results in higher detection accuracies. The proposed technique has been evaluated on the basis of sensitivity (Se), positive predictive value (PPV), & accuracy (Acc) with 99.93% of Se, 99.95% of PPV, & 99.88% of Acc on MIT-BIH Arrhythmia database (M/B Ar DB). The proposed methodology will a long way in assisting the cardiologists in efficient, effective and timely computer-aided diagnosis of irregularities in heart rhythms of a subject (patient).

Keywords Electrocardiogram (ECG) · Fractional Fourier transform (FrFT) · Principal component analysis (PCA) · MIT-BIH Arrhythmia database (M/B Ar DB)

1 Introduction

According to World Health Organization (WHO) reports, cardiac abnormalities are prime cause leading to casualties in the world (Kublanov and Dolganov 2019). In 2008, around 17.3 million people, constituting 30% of the total casualties worldwide, succumbed to cardiac abnormalities (Alwan 2011). For instance, myocardial infarction (MI) has been found to be one of the most frequently occurring cardiac abnormality that is responsible for most of the casualties due to irreversible damage to heart muscles (Vimala and Kalaivani 2014; Aqil et al. 2016). Hence, fast and accurate diagnosis is the need of the hour that is very important to avoid such casualties (Baloglu et al. 2019).

The electrocardiogram (ECG) is an important and primitive diagnostic tool in clinical routine for detecting cardiac abnormalities (Luz et al. 2016; Sharma and Sharma 2016; Sharma and Sunkaria 2016; Sahoo et al. 2017). ECG signal comprises of different waves viz. P, QRS and T waves, which represents electrical potential variations derived from the polarization and depolarization activity of the heart (Manikandan and Soman 2012; Arbateni and Bennia 2014; Liu et al. 2014; Kim et al. 2009; Chen et al. 2006). Unfortunately, the acquisition of ECG data records entails the involvement of various types of noises (Padmavathi and Ramakrishna 2015a, 2016, 2015b; Rakshit and Das 2017; Nallathambi and Principe 2014; Pandit et al. 2017; Choi

✉ Varun Gupta
vargup2@gmail.com

1 Department of Electrical and Electronics Engineering, KIET Group of Institutions, Delhi-NCR, Ghaziabad, Uttar Pradesh 201206, India

2 Department of Electrical Engineering, NIT, Kurukshetra, Haryana 136119, India

3 Department of Electronics and Communication Engineering, NIT, Kurukshetra, Haryana 136119, India

4 Sunder Deep Group of Institutions, Ghaziabad, India

et al. 2010; Mehta et al. 2010; Rekik and Ellouze 2017). But it is an indispensable component of effective computational medicine for detecting heart diseases (Padmavathi and Ramakrishna 2015b; Yakut and Bolat 2018; Yazdani and Vesin 2016).

Traditional techniques of ECG signal analysis are confined mainly to time domain using filtering techniques, morphological techniques, etc. But these are not sufficient to analyze all of its attributes. Additional information about frequency components of an ECG signal is also required for more accurate analysis. In Kaur et al. (2018), self-convolution window (SCW) was used for denoising the ECG signals. They used Hamming window with discontinuous response at the edges. In Leong et al. (2012), quadratic spline wavelet transform was used for developing QRS detection processor. But there, proper identification of singular points was very difficult. In Yochum et al. (2016), automatic detection was performed of all three waves comprising an ECG signal viz. P, QRS, and T using 12 leads acquired ECG signal by using continuous wavelet transform (CWT). But it missed out on necessary phase information.

In Li et al. (2014), two operations were performed on an ECG signal viz. denoising and R-peak detection using empirical mode decomposition (EMD). Unfortunately, EMD operation is not capable of interpreting the hypothesis-driven analyses. In Acharya et al. (2008), modelling technique was used for automatic identification of cardiac health. But that process heavily relied on the chosen model order and corresponding coefficients. In Bahoura et al. (1997), digital signal processing (DSP) implementation was done based on wavelet transform (WT) for analysing real time ECG waveforms. That implementation relied on its multiply–accumulate performance i.e. filtering and frequency response.

In Nygaards and Sornmo (1983), envelope of an ECG signal was used for delineating the QRS complexes. But it needed additional effort in visually inspecting the QRS complexes and corresponding algorithm. In Trahanias (1993), mathematical morphology was used for detecting QRS complex in an ECG signal. But that process entailed higher computational costs. In Plesnik et al. (2012), fiducial points were detected present in an ECG signal using the euclidean distance measure. But sometimes that measure failed being not yielding fruitful results e.g. when the variations in the distance of overall system were not considered. In next research work, Ning and Selesnick (2013) utilized sparse derivatives for ECG enhancement as well as QRS detection. But that required computation of Jacobians and Hessians involving huge mathematical operations alongwith expansion of detection errors due to presence of high-frequency noises. In Verma et al. (2018), Alexander fractional differential window (AFDW) filter was developed based on both forward and backward coefficients for ECG denoising. Unfortunately, AFDW polynomial fails to link all existing pairs of component in some cases. In Das and Ari (2013), an ECG signal was denoised using stockwell transform (S-transform). But there redundancy in S-transform increases for multidimensional ECG signals. In Meireles (2011), adaptive signal processing (ASP) approach was used for ECG signal denoising. But it depended on the selection of reference signal. In Mehta and Lingayat (2008), QRS complexes were recognized using support vector machine (SVM) technique. But performance of SVM is adversely affected due to large amount of noises/distortions. In Altan et al. (2019), Second Order Difference Plots (SODP) technique was used to extract heart rate variability (HRV) features of an ECG for diagnosing different cardiac disorders. But there the performance was also adversely affected due to noisy datasets. In Zhang et al. (2010), Hilbert-Huang transform (HHT) was used for ECG signal denoising. But there blending of empirical modes occurred resulting in mode mixing. In Bouaziz et al. (2014), an improved QRS complex detection algorithm was presented based on wavelet transform (WT). WT (Leong et al. 2012; Yochum et al. 2016) and fractional Fourier transform (FrFT) (Mendlovic and Ozaktas 1993) are two important time–frequency analysis tools that have been frequently used for signal analysis. Performance and effectiveness of WT relies on the choice of two important parameters (Dinh et al. 2002; Chen et al. 2006); (i) mother wavelet; (ii) decomposition level. WT provides information from both frequency and time domains (Dokur and Olmez 2001). Discrete wavelet transform (DWT) is a well-known technique for ECG signal classification due to its easier implementation. Continuous wavelet transform (CWT) has also been used to extract features from the ECG signals (Alyasseri et al. 2018) as it overcomes drawbacks of DWT like coarseness of the representation and instability. However, it has its own limitations such as presence of redundancies, lack of providing phase information needed for reconstructing the original signal, need of correct discretization and high computational cost. Also, WT based techniques suffer due to fringing effects and phase shift problems (Sunkaria et al. 2010).

It has been observed from the above literature survey that until now a huge portion of the biomedical research spectrum has been devoted for exploring ECG signal processing techniques to facilitate early and timely diagnosis. Correct detection of R-peaks (QRS complexes) can effectively lead to an accurate diagnosis of the cardiac abnormalities. But their detection by manual inspection is cumbersome due to time-varying morphology, physiological variations of the patient & noise and needs a skilled observer introducing additional inter-observer variabilities. Therefore, computer aided diagnosis based on an efficient feature extraction algorithm can provide the solution. Additionally in the literature, majority of the existing techniques for ECG signal analysis relied heavily on its pre-processing that is computationally expensive prohibiting their usage on portable ECG devices, which normally lack sufficient computational resources.

Therefore, fractional Fourier transform (FrFT) is proposed to be used in this paper for effective feature extraction in the time-fractional-frequency domain through its filtering effect that also facilitates easier noise separation. The novelty of the present work to efficiently detect R-peaks in the presence of various types of noise/distortions/physiological variabilities using raw ECG datasets without any pre-processing/filtering technique. Principal component analysis (PCA) is proposed to be utilized for detecting R-peaks with higher accuracies based on the obtained eigenvalues and eigenvectors, which belong to a new orthogonal basis (Chawla 2008).

The paper is structured as; Sect. 2 provides details of the used database(s), feature extraction using FrFT, detection using PCA and definition of evaluation parameters. Section 3 showcases and discusses some important obtained results followed by conclusion at the end.

2 Materials and methods

In this section, details of the used ECG database, feature extraction technique, detection technique, and performance evaluating parameters are presented.

Figure 1 shows the technique proposed in this paper.

2.1 ECG database

During last three decades, MIT-BIH arrhythmia (M/B Ar DB) database has been widely used (Sunkaria et al. 2010; Rodriguez et al. 2015; Zidelmal et al. 2012) by majority of researchers from different countries. Therefore in this paper, the same database viz. M/B Ar DB is used to provide suitable comparisons with the results reported in other similar existing studies.

2.2 Feature extraction using fractional Fourier transform (FrFT)

FrFT is one of the most widely used technique among other existing signal processing tools that provides both time and frequency information along the intermediate axis that lie at a certain angle (α) with the reference time axis (Ozaktas et al. 2001; Lin et al. 2004; Daamouche et al. 2012). This rotation angle is measured in counterclockwise direction of rotation of u axis w.r.t time axis. It's value lies between 0 and $\frac{\pi}{2}$ and it provides time–frequency description of the signal (Lin 1999; Singh and Singh 2017; Sejdic et al. 2009; Pipberger et al. 1990) in the intermediate domain created by the rotating vector as shown in Fig. 2.

Mathematically, pth ($p = 2\alpha/\pi$) order FrFT of a signal $x(t) \in L^2(R)$ is defined as (Zayed 1996)

$$X_p(u) = F^p\{x(t)\}(u) = \int_{-\infty}^{\infty} x(t) K_p(t,u)\,dt \quad (1)$$

$$\text{where } K_p(t,u) = \sqrt{\frac{1 - j\cot\alpha}{2\pi}} \exp\left(j\frac{t^2 + u^2}{2}\cot\alpha - jut\csc\alpha\right), \text{ when } \alpha \neq k\pi \quad (2)$$

$$K_p(t,u) = \delta(u - t), \text{ when } \alpha = 2k\pi \quad (3)$$

$$K_p(t,u) = \delta(u + t), \text{ when } \alpha = (2k+1)\pi \quad (4)$$

Frequency analysis makes it easier to handle frequency sensitive additives like noise/distortion. FrFT has been proposed to be applied for ECG signal analysis in this paper

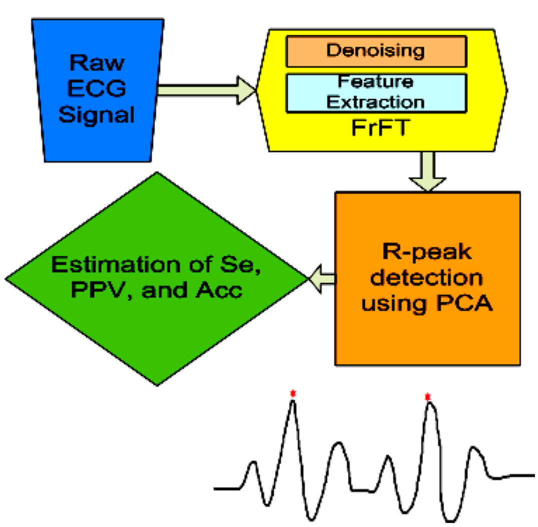


Fig. 1 Proposed technique

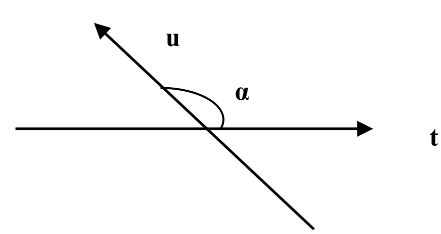
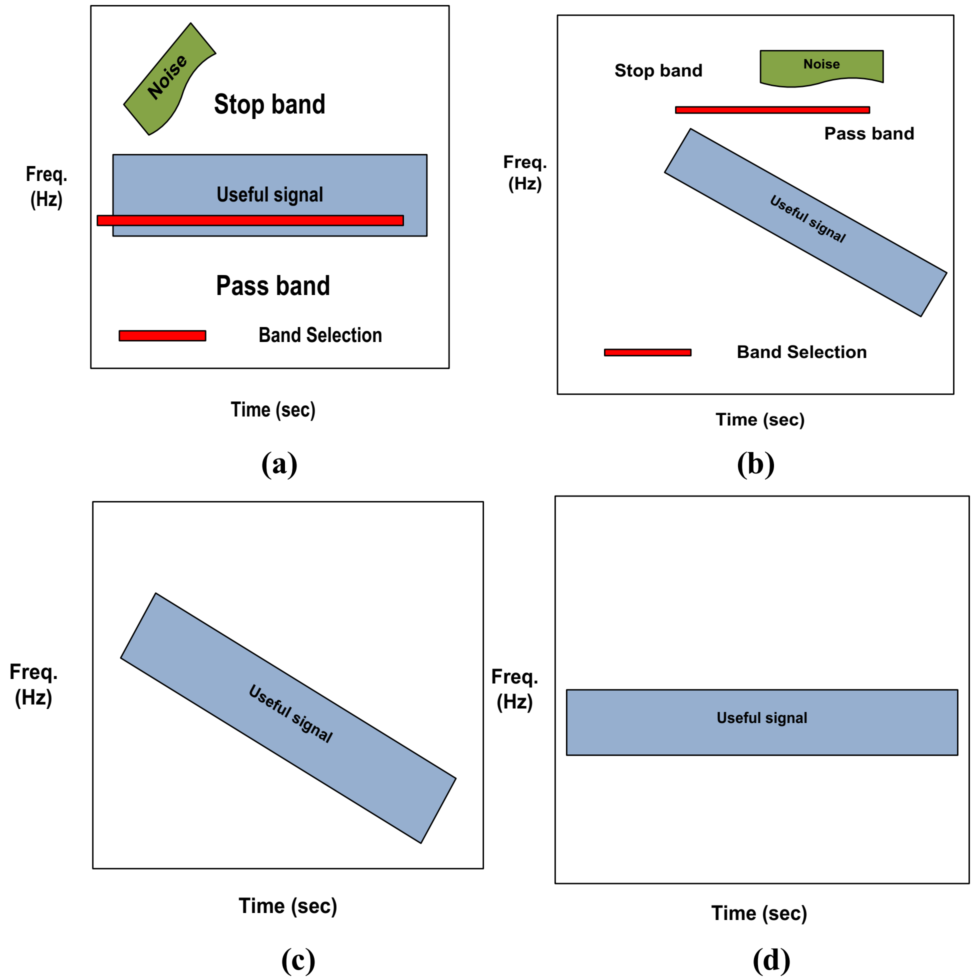


Fig. 2 The angle of rotation of α

Fig. 3 Filtering effect of FrFT **a** Raw ECG signal, **b** FrFT at rotation angle $0 < \alpha < \pi/2$, **c** filtered signal, and **d** original ECG signal after rotation without noise



for both extracting the features and denoising as shown in Fig. 3. It transforms a signal (either from time or frequency domain) into an intermediate domain between time and frequency. Infact, the signal is rotated in time–frequency domain which has a filtering effect resulting in retention of original pathological information (Pipberger et al. 1990). Figure 3 shows the above mechanism. In Fig. 3a, it is clearly shown that if basic (ordinary) filter is used, then useful clinical information is lost during selection of passband and stopband (shown by red boundary for more clarity). But after fractional Fourier transform (FrFT), noise gets separated easily due to rotation at an angle enabling effective filtering with effective feature extraction in time-fractional-frequency domain (Fig. 3b and c) yielding original recorded ECG signal without noise which retains all pathological information (Fig. 3d).

After feature extraction step, R-peak detection is performed using PCA as illustrated in next subsection.

2.3 Principal component analysis (PCA)

PCA is well known for trimming the dimensions of new variables without loosing any information. The new set of variables are called principal components (PCs) (Chawla 2008). All PCs are orthogonal in nature and are formulated based on supremum of eigenvalues (i.e. highest absolute value of an eigenvalue) (Rodriguez et al. 2015). In PCA, whole analysis relies on the value of eigenvalue, eigenvector and variance calculation (Gupta and Mittal 2019a). In this study, average first principal component (PC1) eigenvalue was 98.77% as observed for the whole M/B Ar DB. Detection process has been considered to consist of identifying two categories of patients viz. normal and abnormal.

In the first step, covariance (Cov) is calculated as (Gupta and Mittal 2019b)

$$\text{Covariance(Cov)} = \frac{\sum_{i=1}^{n} \left(x_i - \overline{x}\right)\left(y_i - \overline{y}\right)}{(n-1)} \tag{5}$$

In the second step, eigenvectors are computed using H

$$H^{-1}CovH = \wedge \tag{6}$$

where ^ denotes a diagonal matrix.

In the last step, projected data i.e. PCs are computed as

$$\text{Principal Components(PC)} = [H^{T}\left(x - \overline{x}\right)^{T}]^{T} \tag{7}$$

The performance of the proposed technique is adjudged on the basis of various performance parameters such as sensitivity, positive predictive value, and accuracy as defined in next subsection.

2.4 Performance evaluating parameters

The performance of the proposed technique for R-peak detection is evaluated using different parameters (Kaya et al. 2017; Kaya and Pehlivan 2015a; Phukpattaranont 2015; Thakor and Zhu 1991; Kaya and Pehlivan 2015b; Gupta and Mittal 2019c; Gupta and Mittal 2020; Gupta and Mittal 2021) which are mathematically explained as

$$\text{Sensitivity(Se)} = \frac{TP}{TP + FN} \tag{8}$$

$$\text{Positive Predictive Value (PPV)} = \frac{TP}{TP + FP} \tag{9}$$

$$\text{Accuracy(Acc)} = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

where TP is the number of 'True Positive' which signifies correctly detected R-peaks, TN is the number of 'True Negative' which signifies correct identification of non R-peaks, FN is the 'False Negative' which signifies number of R-peaks that were not detected by the proposed technique, and FP is the 'False Positive' that signifies wrongly detected R-peaks.

3 Results and discussion

Efficacy of the analysis of an ECG signal heavily relies on variety of noises and artifacts that creep in during its recording. Therefore, an efficient pre-processing stage is required under such circumstances, but that further increases computation cost of the automated ECG signal analysis. In this paper, the proposed technique obviates the need of the pre-processing stage and the whole operation has been performed on the features extracted using FrFT followed by detection using PCA. This helps in lowering down the computational cost. The raw ECG signal is shown in Fig. 4. Real and imaginary parts of FrFT and its inverse operation are shown in Figs. 5 and 6, respectively. Figure 6 showcases the transformation characteristics of FrFT i.e. its capability to recover the original signal upon taking its inverse. This will enable the users to utilize the signal obtained after inverse FrFT for R-peaks detection. Detected wave components in the ECG signal according to variance calculation and R-peaks for M/B Ar DB are shown in Figs. 7 and 8, respectively.

Five different features viz. R-peaks, T waves, P waves, BLW, and noise components have been considered in this paper during detection. It can be observed from Fig. 7 that R-peaks, T-waves, P-waves, BLW and noise components (viz. EMG, PLI, low, and high frequency) are detected with a variance of 98.77%, 37.11%, 21.22%, 5.22% and 1.2%, respectively sequentially one after another in the decreasing order from desirable to undesirable components. This

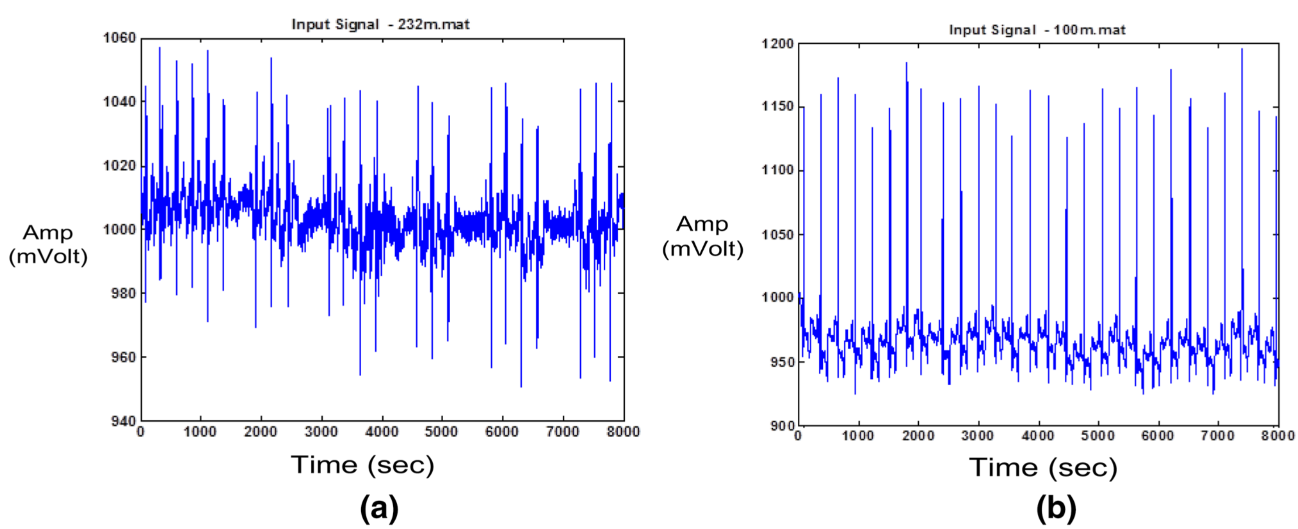


Fig. 4 Raw ECG signal from M/B Ar DB **a** dataset no. 232 m, **b** dataset no. 100 m

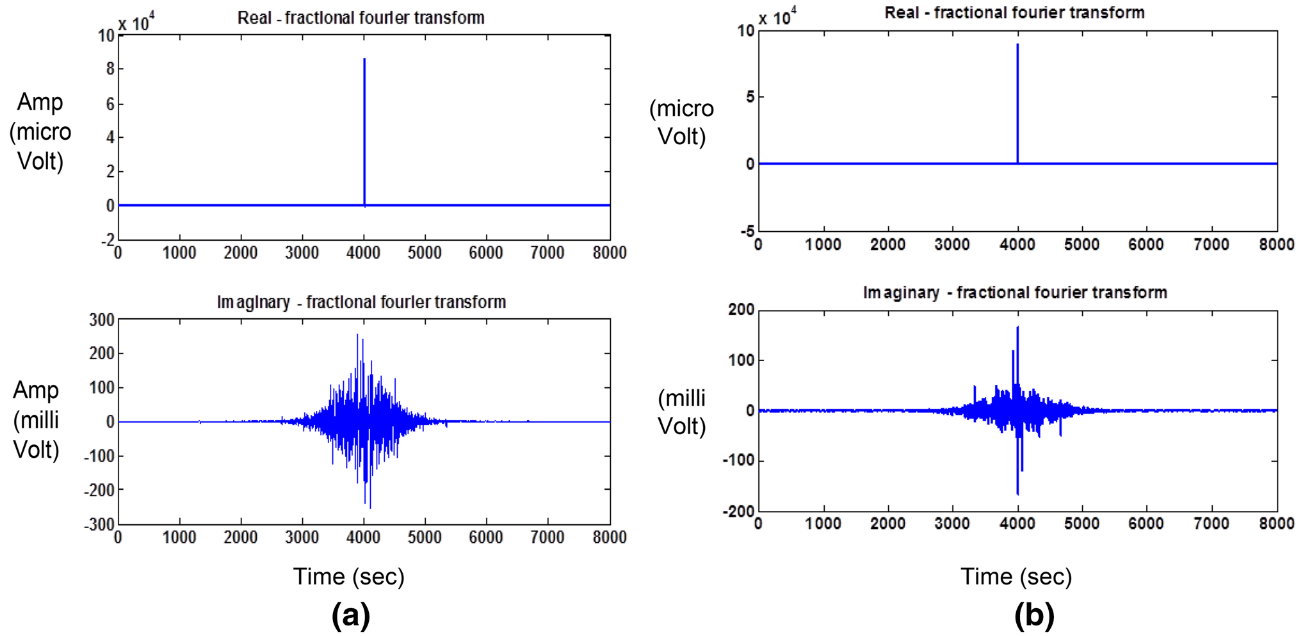


Fig. 5 Real and imaginary part of FrFT for **a** dataset no. 232 m, **b** dataset no. 100 m

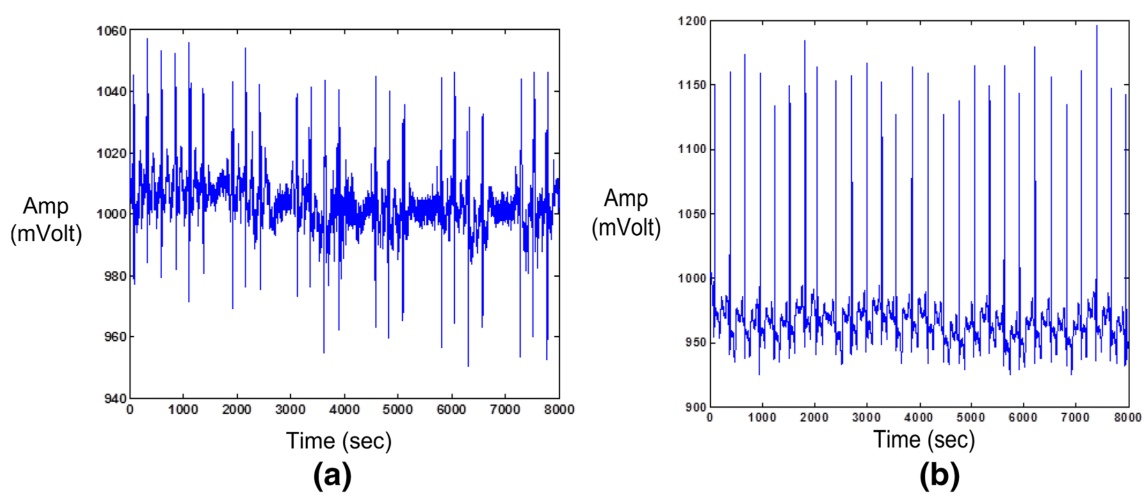


Fig. 6 Inverse operation of FrFT for **a** dataset no. 232 m, **b** dataset no. 100 m

establishes the fact that PCA reduces the dimensions of selected features facilitating detection of R-peaks in different datasets on the basis of estimated variance of first principal component i.e. PC1.

Figure 8a shows R-peaks detection using PCA for M/B Ar DB record no. 232 m containing a total of 1777 R-peaks (shown in Table 1) with 1776 detected R-peaks and true positives (TPs), 01 false negatives (FNs) and zero both false positives (FPs) and true negatives (TNs). The detected six small peaks consist of five actual R-peaks and one FN. This result demonstrate strength of the proposed method that actual R-peaks hidden even in the smaller ECG signal peaks are detected with very small detection error e.g. as 01 in 1777 for 232 m data record. Similarly, all of the actual R-peaks (i.e. 2270) were detected with zero FN, FP and TN for the record no. 100 m as shown in Fig. 8b and summarized in Table 1. Figure 8c shows R-peak detection in dataset no. 100 m for a time duration of 3 s using PCA (where 3 R-peaks are shown by blue color arrow).

Table 1 shows the detected R-peaks, TPs, FNs, FPs and TNs obtained using the proposed technique. It is revealed that datasets such as 100 m, 103 m, 107 m, 109 m, 115 m,

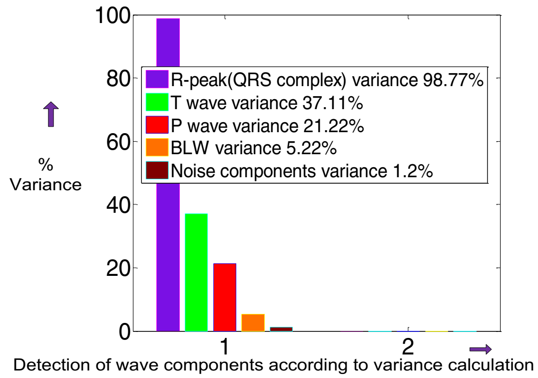


Fig. 7 Detection of wave components as per variance

117 m, 119 m, 123 m, 124 m, 212 m, 219 m, 220 m, 230 m, 231 m, attain Se, PPV, and Acc of 100% due to less detection error (FN and FP) in the proposed technique.

Table 2 summarizes the findings and compare them with other existing state-of-the-art techniques on the basis of evaluation parameters viz. Se, PPV and Accuracy. It is observed that the proposed technique outperforms the existing techniques on the basis of these parameters in general. Despite of Se having similar values (e.g. in Manikandan and Soman 2012; Rakshit and Das 2017), the values of PPV and Acc are less. Therefore, it can be concluded that out of all the compared techniques, only the proposed technique provides higher values of all the assessment parameters simultaneously.

Table 3 summarizes the overall comparison of the proposed and other existing techniques on the basis of Total beats, TP and FN + FP for the entire M/B Ar DB. It is observed from Table 3 that the overall performance of the proposed technique is better as compared to that of the existing techniques.

Table 4 outlines merits and demerits of the proposed and existing techniques. It indicates that the proposed technique has low computational cost as the pre-processing stage is skipped without compromising important clinical attributes.

The selected assessment parameters in this paper viz. Se, PPV and Acc indicate robustness of a technique in the context of duplicity (D), which exists in the detection results, if

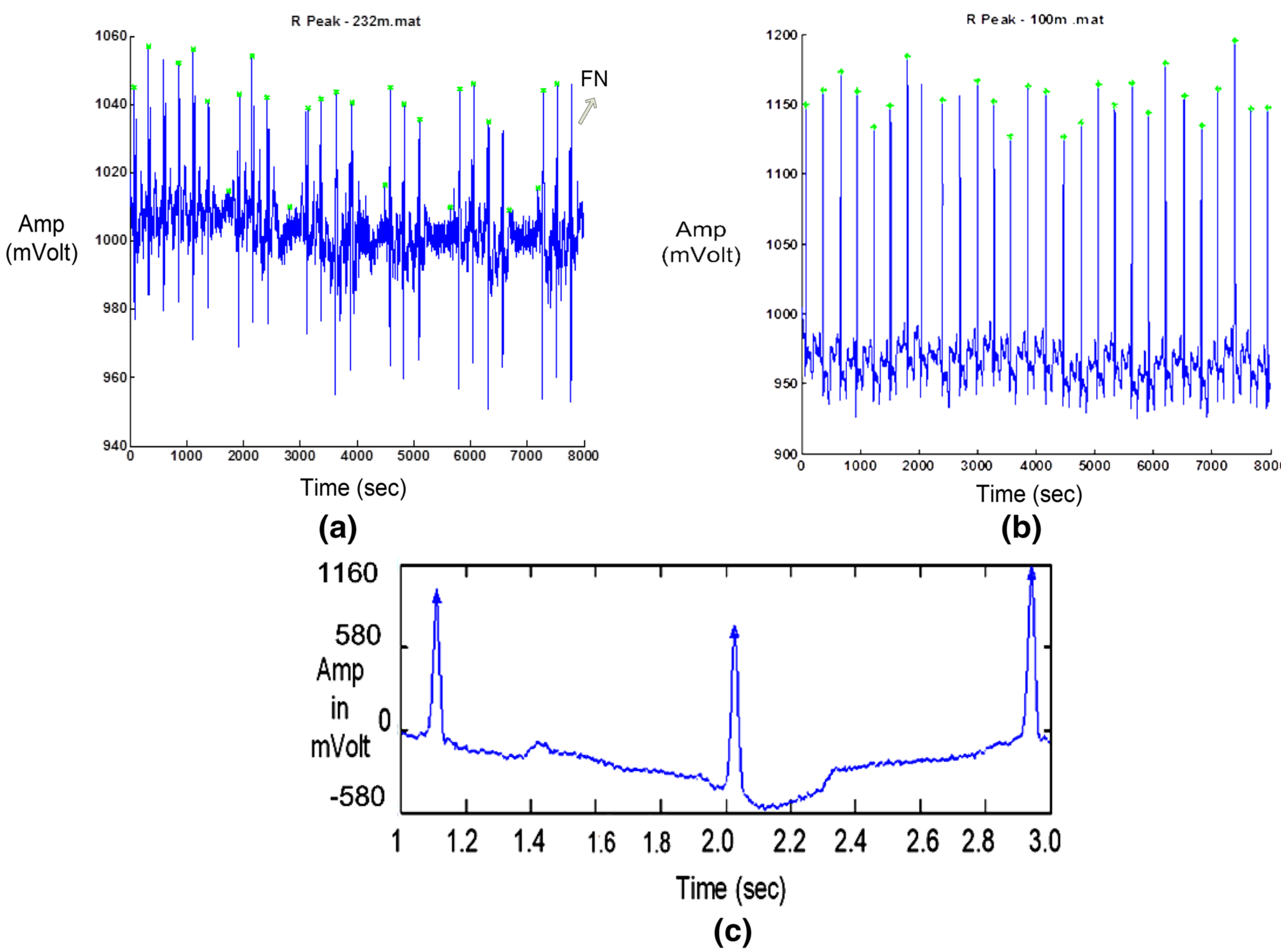


Fig. 8 R-peak detection in **a** whole dataset no. 232 m, **b** whole ataset no. 100 m **c** for 3 s duration of dataset no. 100 m

Table 1 TP, FN, FP and TN calculation after applying FrFT and PCA

M/B Ar DB	Actual R-peak	Detected R-peak	TP	FN	FP	TN
100 m	2270	2270	2270	0	0	0
101 m	1867	1866	1866	1	0	0
102 m	2187	2186	2186	1	1	0
103 m	2081	2081	2081	0	0	0
104 m	2233	2231	2231	2	3	0
105 m	2589	2581	2582	5	4	1
106 m	2038	2036	2036	2	1	0
107 m	2144	2144	2144	0	0	0
108 m	1773	1772	1772	7	4	0
109 m	2535	2534	2534	0	0	1
111 m	2126	2125	2125	1	1	0
112 m	2539	2538	2537	0	3	0
113 m	1797	1796	1795	1	1	0
114 m	1885	1884	1884	1	1	0
115 m	1957	1957	1957	0	0	0
116 m	2413	2411	2411	3	1	0
117 m	1541	1541	1541	0	0	0
118 m	2276	2275	2275	2	0	1
119 m	1981	1981	1981	0	0	1
121 m	1871	1870	1870	1	1	0
122 m	2477	2477	2476	0	1	0
123 m	1532	1531	1531	0	0	1
124 m	1632	1632	1632	0	0	0
200 m	2611	2607	2607	6	4	0
201 m	1972	1971	1971	0	1	1
202 m	2137	2135	2135	3	1	1
203 m	2983	2976	2978	7	6	1
205 m	2661	2659	2659	3	2	0
207 m	2331	2328	2329	5	3	0
208 m	2955	2952	2952	4	3	0
209 m	3012	3012	3011	1	0	0
210 m	2652	2648	2647	8	6	0
212 m	2753	2753	2753	0	0	0
213 m	3258	3257	3258	1	1	0
214 m	2271	2271	2270	0	1	1
215 m	3377	3376	3376	2	1	1
217 m	2213	2212	2212	1	1	0
219 m	2159	2158	2158	0	0	1
220 m	2067	2067	2067	0	0	1
221 m	2426	2425	2426	1	0	0
222 m	2483	2482	2482	1	1	0
223 m	2604	2603	2603	1	0	0
228 m	2052	2050	2050	5	4	0
230 m	2255	2255	2255	0	0	0
231 m	1569	1569	1569	0	0	0
232 m	1777	1776	1776	1	0	0
233 m	3078	3077	3077	2	1	0
234 m	2748	2746	2746	1	0	1
Total 48 Rec	**1,10,148**	**1,10,084**	**1,10,084**	**80**	**58**	**13**

Bold signifies to proposed work

Table 2 Comparison of the proposed and existing techniques for M/B Ar DB

References	Technique	Se (%)	PPV (%)	Acc (%)
Proposed	**Fractional Fourier transform (FrFT) and Principal Component Analysis (PCA)**	**99.93**	**99.95**	**99.88**
Manikandan and Soman (2012)	Hilbert-transform (HT) and moving average (MA) filter	99.93	99.86	99.79
Arbateni and Bennia (2014)	Sigmoidal radial basis function ANN	99.82	99.91	99.70
Rakshit and Das (2017)	Wavelet with Hilbert transform	99.93	99.91	99.83
Nallathambi and Principe (2014)	Integrate and fire pulse train automaton	99.58	99.55	99.12
Pandit et al. (2017)	Max-min difference algorithm	99.65	99.66	99.31
Bouaziz et al. (2014)	Multiresolution wavelet	99.87	99.79	-
Rodriguez et al. (2015)	Hilbert transform, adaptive threshold technique and PCA	96.28	99.71	-
Zidelmal et al. (2012)	Wavelet coefficients	99.64	99.82	-
Thakor and Zhu (1991)	Weighted total variation	99.90	99.88	99.77
Zidelmal et al. (2014)	S-transform and shannon energy	99.84	99.91	-
Sahoo et al. (2016)	Hilbert transform and adaptive thresholding	99.71	99.72	-
Afonso et al. (1999)	Filter banks	99.59	99.56	-
Kaya and Pehlivan (2015a, b)	KNN and GA95	99.46	-	99.69

Bold signifies to proposed work

Table 3 Comparison of the proposed and existing techniques on the basis of total beats, TP, and (FN + FP)

Reference	Technique	Total Beats	TP	FN + FP
Proposed	**Fractional Fourier transform (FrFT) and principal component analysis (PCA)**	**1,10,148**	**1,10,084**	**138**
Manikandan and Soman (2012)	Hilbert-transform (HT) and moving average (MA) filter	1,09,496	1,09,417	219
Arbateni and Bennia (2014)	Sigmoidal radial basis function ANN	1,09,483	1,09,273	319
Rakshit and Das (2017)	Wavelet with Hilbert transform	1,09,494	1,09,410	183
Nallathambi and Principe (2014)	Integrate and fire pulse train automaton	1,09,494	1,09,032	957
Pandit et al. (2017)	Max-Min difference algorithm	1,09,809	1,09,432	758
Phukpattaranont (2015)	Quadratic filter	1,09,483	1,09,281	412
Thakor and Zhu (1991)	Adaptive filtering	1,09,494	1,09,381	249
Pan and Tompkins (1985)	Digital band pass filtering	1,09,809	1,09,208	784
Sharma et al. (2019)	Tunable-Q wavelet transform	1,09,494	1,09,363	314

Bold signifies to proposed work

total detected beats (TP + FN + FP + TN) are higher as compared to total actual beats. It should be as low as possible in detection/classification type problems. It is observed that Zidelmal et al. (2012), Sharma and Sharma (2017), Saini et al. (2013), and Dohare et al. (2013) have reported the duplicity of 0.1762%, 0.1242%, 0.1373%, and 0.6620%, respectively. On the other hand, the proposed technique has duplicity of 0.0789%. Therefore, it can be concluded that the proposed technique outperforms the existing techniques on this count also. These results indicate that quality of biology-related information is retained in the FrFT features extracted from an ECG signal for identifying different heart abnormalities alongwith other benefit of FrFT such as denoising, time-fractional-frequency portrays, etc.

4 Conclusion

The proposed technique has been implemented successfully on M/B Ar DB yielding Se of 99.93%, PPV of 99.95%, and Acc of 99.88%, which are consistently of higher values unlike one or two parameters (at the most of equal value) provided by the existing techniques at one point of time. The proposed technique also achieves a FN + FP of 138, and D of 0.0789%, which are least among the existing techniques. As ECG signal processing has three main pillars viz. preprocessing, feature extraction, and detection. The obtained results demonstrates that FrFT fulfills the need of both efficient pre-processing and feature extraction whereas PCA effectively detects R-peaks in both situations of the patient

Table 4 Comparison of the proposed and existing techniques on the basis of relative merits/demerits

References	Technique	Merits	Demerits
Proposed	FrFT with PCA	(i) No pre-processing technique is needed separately (ii) Low computational cost (iii) Low duplicity (iv) Low detection error or false detection (FN + FP) (v) High Se, PPV, and Acc	(i) Not suitable for locating Fractional Fourier Domain (FrFD) frequency contents
Sunkaria et al. (2010)	Wavelet transform (WT)	(i) It can be implemented on the basis of spectral characteristics as well as morphology of QRS complex in the ECG signal (ii) It offers simultaneous localization in both time and frequency domains (iii) It can compress a signal without appreciable degradation	(i) It is computationaly intensive where fine analysis is required more (ii) Not having shift invariance property (iii) Its accuracy is dependent on the selection of the type of wavelet basis function, threshold type, and decomposition level
Padmavathi et al. (2017)	Sequency ordered complex hadamard transform and hybrid firefly algorithm	(i) Fast computation (ii) Easy to apply (iii) Sequence structure	(i) More difficult to show key outcomes (ii) Higher chances of being trapped in local optimum (iii) Easy to fall into stagnation
Acharya et al. (2017)	Convolutional neural network (CNN)	(i) Invariant to translation (ii) No pre-processing is needed	(i) Hyper-parameter tuning is non-trivial (ii) Requires large datasets for efficient training (iii) Performance is highly depends on initially tunned parameters
Padmavathi and Ramakrishna (2014)	Magnitude squared coherence and support vector machine (SVM)	(i) Higher spectral resolution (ii) Avoids the signal mismatch problem (iii) It can be utilized for finding phase difference between two signals (iv) Low risk of over-fitting	(i) High spikes in non-sampled frequencies are not detected (ii) Requires the estimation of a large number of frequencies (iii) Requires high CPU time (iv) Requires long training time for large datasets (v) Difficult tointerpret the final model, variable weights and individual impact
Gupta et al. (2019c)	Chaos theory	(i) Presents optimal trajectory for segregating noise and type of arrhythmia (ii) No pre-processing is needed	Requires proper selection of – (i) initial values, (ii) Euclidean distance (iii) Lyapunov exponents (iv) correlation dimension, and mutual information
Padmavathi (2017)	Hybrid firefly algorithm	(i) Good efficiency (ii) Higher flexibility (iii) High speed of convergence	(i) Unable to detect distinct types of arrhythmias (ii) Computational time may increase incase of signal is having very low and very high frequency (noise) components (iii) Higher chances of being trapped in local optimum

being normal/abnormal. This signify its effectiveness for analyzing the time-varying signals. The proposed technique is also expected to reduce the computational time because pre-processing has not been used separately for denoising the raw ECG signal.

Though FrFT is effective for analyzing time-varying signals but it is not suitable for locating fractional Fourier domain (FrFD) frequency contents, which is an important aspect. Also, it cannot detect the local structures present in the signal. Despite this shortcoming, the present paper has proposed its efficient utilization for detecting R-peaks in an ECG signal facilitating arrhythmias detection implicitly. In future, the proposed technique may be improvised suitably for explicit and timely detection of the presence of arrhythmias.

Data availability Available on physionet website (https://physionet.org).

References

Acharya UR, Sankaranarayanan M, Nayak J, Xiang C, Tamura T (2008) Automatic identification of cardiac health using modeling techniques: a comparative study. Info Sci 178(23):4571–4582

Acharya UR, Fujita H, Lih OS, Hagiwara Y, Tan JH, Adam M (2017) Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network. J Inf Sci 405:81–90

Afonso VX, Tompkins WJ, Nguyen TQ, Luo S (1999) ECG beat detection using filter banks. IEEE Trans Biomed Eng 46(2):192–202

Altan G, Kutlu Y, Yeniad M (2019) ECG based human identiþcation using second order difference plots. Comput Methods Prog Biomed 170:81–93

Alwan A (2011) Global status report on noncommunicable diseases. World Health Organization, Geneva, pp 9–31

Alyasseri ZAA, Khader AT, Betar MAA, Awadallah MA (2018) Hybridizing β-hill climbing with wavelet transform for denoising ECG signals. Info Sci 429:229–246

Aqil M, Jbari A, Bourouhou A (2016) Adaptive ECG Wavelet analysis for R-peaks Detection. In: 2016 International Conference on Electrical and Information Technologies (ICEIT), pp 1–4

Arbateni K, Bennia A (2014) Sigmoidal radial basis function ANN for QRS complex detection. Neurocomputing 145(5):438–450

Bahoura M, Hassani M, Hubin M (1997) DSP implementation of wavelet transform for real time ECG waveforms detection and heart rate analysis. J Comput Meth Prog Biomed 52(1):35–44

Baloglu UB, Talo M, Yildirim O, Tan RS, Acharya UR (2019) Classification of myocardial infarction with multi-Lead ECG signals and deep CNN. Pattern Recogn Lett 122:23–30

Bouaziz F, Boutana D, Benidir M (2014) Multiresolution wavelet-based QRS complex detection algorithm suited to several abnormal morphologies. IET Signal Proc 8(7):774–782

Chawla MPS (2008) Segment classification of ECG data and construction of scatter plots using principal component analysis. J Mech Med Bio 8(3):421–458

Chen SW, Chen CH, Chan HL (2006) A real-time QRS method based on moving-averaging incorporating with wavelet denoising. Comput Methods Prog Biomed 82(3):187–195

Choi S, Adnane M, Lee GJ, Jang H, Jiang Z, Park HK (2010) Development of ECG beat segmentation method by combining lowpass filter and irregular R-R interval checkup strategy. Exp Syst Appl 37(7):5208–5218

Daamouche A, Hamami L, Alajlan N, Melgani F (2012) A wavelet optimization approach for ECG signal classification. Biom Signal Proc Control 7(4):342–349

Das M, Ari S (2013) Analysis of ECG signal denoising method based on S-transform. IRBM 34(6):362–370

Dinh AN, Kumar DK, Pah ND, Burton P (2002) Wavelet for QRS detection. In: 2002 International Conference on Engineering in medicine and Biology society, pp 7803–7811

Dohare AK, Kumar V, Kumar R (2013) An efficient new method for the detection of QRSin electrocardiogram. Comput Electr Eng 40(5):1–9

Dokur Z, Ölmez T (2001) ECG beat classification by a novel hybrid neural network. Comput Methods Prog Biomed 66(3):167–181

Gupta V, Mittal M (2019a) R-peak detection in ECG signal using Yule-Walker and principal component analysis. IETE J Res. https://doi.org/10.1080/03772063.2019.1575292

Gupta V, Mittal M, Mittal V (2019b) R-peak detection using chaos analysis in standard and real time ECG databases. IRBM 40(6):341–354

Gupta V, Mittal M (2019c) QRS complex detection using STFT, chaos analysis, and PCA in standard and real-time ECG databases. J Inst Eng India Ser B 100:489–497

Gupta V, Mittal M (2020) A novel method of cardiac arrhythmia detection in electrocardiogram signal. Int J Med Eng Inf (IJMEI) 12(5):489–499

Gupta V, Mittal M (2021) R-peak detection for improved analysis in health informatics. Int J Med Eng Inf (IJMEI) 13(3):213–223

Kaur A, Agarwal A, Agarwal R, Kumar S (2018) A novel approach to ECG R-peak detection. Arab J Sci Eng 44:6679–6691

Kaya Y, Pehlivan H (2015a) Feature selection using genetic algorithms for premature ventricular contraction classification. In: 2015 International Conference on Electrical and Electronics Engineering, pp 1229–1232

Kaya Y, Pehlivan H (2015b) Classification of premature ventricular contraction in ECG. Int J Adv Comput Sci Appl 6:34–40

Kaya Y, Pehlivan H, Tenekeci ME (2017) Effective ECG beat classification using higher order statistic features and genetic feature selection. J Biomed Res 28:7594–7603

Kim J, Shin HS, Shin K, Lee M (2009) Robust algorithm for arrhythmia classification in ECG using extreme learning machine. Bio Med Eng Online 8(31):1–12

Kublanov V, Dolganov A (2019) Development of a decision support system for neuro-electrostimulation: diagnosing disorders of the cardiovascular system and evaluation of the treatment efficiency. Appl Soft Comput 77:329–343

Leong CI, Mak PI, Lam CP, Dong C, Vai MI, Mak PU, Pun HS, Wan F, Martins RP (2012) A 0.83μW QRS detection processor using quadratic spline wavelet transform for wireless ECG acquisition in 0.35 m CMOS. IEEE Trans Biomed Circuits Syst 6(6):586–595

Li H, Wang X, Chen L, Li E (2014) Denoising and R-peak detection of electrocardiogram signal based on EMD and improved approximate envelope. Circuit Syst Sig Process 33(4):1261–1276

Lin PY (1999) The fractional Fourier transform and its applications. National Taiwan University, Taiwan, pp 23–54

Lin Q, Ran T, Siyong Z, Yue W (2004) Detection and parameter estimation of multicomponent LFM signal based on the fractional Fourier transform. Sci China Ser F Info Sci 47(2):184–198

Liu X, Yang J, Zhu X, Zhou S, Wang H, Zhang H (2014) A novel R-Peak detection method combining energy and wavelet transform in electrocardiogram signal. J Biom Eng 26:1–9

Luz EJS, Schwartz WR, Cháveza GC, Menotti D (2016) ECG-based heartbeat classification for arrhythmia detection: a survey. Comp Meth Prog Biomed 127:144–164

Manikandan MS, Soman KP (2012) A novel method for detecting R-peaks in the electrocardiogram (ECG) signal. Biomed Signal Proc Cont 7(2):118–128

Mehta SS, Lingayat NS (2008) SVM-based algorithm for recognition of QRS complexes in electrocardiogram. IRBM 29(5):310–317

Mehta SS, Shete DA, Lingayat NS, Chouhan VS (2010) K-means algorithm for the detection and delineation of QRS-complexes in electrocardiogram. IRBM 31:48–54

Meireles AJMD (2011) ECG denoising based on adaptive signal processing technique. M.Tech dissertation, Dept. Electronics and Computer Science, Porto, Portugal
Mendlovic D, Ozaktas HM (1993) Fractional Fourier transforms and their optical implementation. J Opt Soc Am A 10(9):1875–1881
Nallathambi G, Príncipe JC (2014) Integrate and fire pulse train automaton for QRS detection. IEEE Trans Biomed Eng 61(2):317–326
Ning X, Selesnick IW (2013) ECG enhancement and QRS detection based on sparse derivatives. Biomed Sig Proc Control 8(6):713–723
Nygåards ME, Sörnmo L (1983) Delineation of the QRS complex using the envelope of the ECG. J Med Biol Eng Comput 21(5):538–547
Ozaktas HM, Zalevsky Z, Kutay MA (2001) The fractional Fourier transform with applications in optics and signal processing. Wiley, New York
Padmavathi K (2017) ECG based myocardial infarction detection using hybrid firefly algorithm. Comput Methods Prog Biomed 152:141–148
Padmavathi K, Ramakrishna KS (2014) Myocardial infarction detection using magnitude squared coherence and support vector machine. In: 2014 International Conference on Medical Imaging, m-Health and Emerging Communication Systems (MedCom), pp 382–385
Padmavathi K, Ramakrishna KS (2015a) Detection of atrial fibrillation using continuous wavelet transform and wavelet coherence. Int J Syst Control Commun 6(4):292–304
Padmavathi K, Ramakrishna KS (2015b) Detection of atrial fibrillation using autoregressive modelling. Int J Electr Comput Eng 5(1):64–70
Padmavathi K, Ramakrishna KS (2016) ECG based heart Arrhythmia detection using wavelet coherence and bat algorithm. Sens Imaging 17(12):1–16
Padmavathi K, Annavarapu A, Yadlapalli P, Ramakrishna KS, Somalaraju V (2017) ECG based atrial fibrillation detection using sequency ordered complex hadamard transform and hybrid firefly algorithm. Eng Sci Tech 20(3):1084–1091
Pan J, Tompkins WJ (1985) A real-time QRS detection algorithm. IEEE Trans Biomed Eng 32:230–236
Pandit D, Zhang L, Liu C, Chattopadhyay S, Aslam N, Lim CP (2017) A lightweight QRS detector for single lead ECG signals using a max-min difference algorithm. Comput Methods Prog Biomed 144:61–75
Phukpattaranont P (2015) QRS detection algorithm based on the quadratic filter. Exp Syst Appl 42(11):4867–4877
Pipberger HV, McManus CD, Pipberger HA (1990) Methods of ECG interpretation in the AVA program. Methods Inf Med 29(4):337–340
Plesnik E, Malgina O, Tasic JF, Zajc M (2012) Detection of the electrocardiogram fiducial points in the phase space using the Euclidian distance measure. Med Eng Phys 34(4):524–529
Rakshit M, Das S (2017) An efficient wavelet-based automated R-Peaks detection method using Hilbert transform. Biocybern Biomed Eng 37(3):566–577
Rekik S, Ellouze N (2017) Enhanced and optimal algorithm for QRS Detection. IRBM 38(1):56–61
Rodríguez R, Mexicano A, Bila J, Cervantes S, Ponce R (2015) Feature extraction of electrocardiogram signals by applying adaptive threshold and principal component analysis. J Appl Res Technol 13(2):261–269
Sahoo S, Biswal P, Das T, Sabut S (2016) De-noising of ECG signal and QRS detection using Hilbert transform and adaptive thresholding. Proc Technol 25:68–75
Sahoo S, Kanungo B, Behera S, Sabut S (2017) Multiresolution wavelet transform based feature extraction and ECG classification to detect cardiac abnormalities. Measurement 108:55–66
Saini I, Singh D, Khosla A (2013) QRS detection using K-Nearest Neighbor algorithm (KNN) and evaluation on standard ECG databases. J Adv Res 4(4):331–344
Sejdic E, Djurovic I, Jiang J, Stankovic LJ (2009) Time-Frequency based feature extraction and classification: considering energy concentration as a feature using stockwell transform and related approaches. VDM Verlag Publishing, Saarbrücken
Sharma T, Sharma KK (2016) QRS complex detection in ECG signals using the synchrosqueezed wavelet transform. IETE J Res 62(6):885–892
Sharma T, Sharma KK (2017) QRS complex detection in ECG signals using locally adaptive weighted total variation denoising. Comp Biol Med 87:187–199
Sharma LD, Sunkaria RK (2016) A robust QRS detection using novel pre-processing techniques and kurtosis based enhanced efficiency. Measurement 87:194–204
Sharma A, Patidar S, Upadhyaya A, Acharya UR (2019) Accurate tunable-Q wavelet transform based method for QRS complex detection. Comput Electr Eng 75:101–111
Singh U, Singh SN (2017) Application of fractional fourier transform for classification of power quality disturbances. IET Sci Meas Technol 11(1):67–76
Sunkaria RK, Saxena SC, Kumar V, Singhal AM (2010) Wavelet based R-peak detection for heart rate variability studies. J Med Eng Technol 34(2):108–115
Thakor NV, Zhu YS (1991) Applications of adaptive filtering to ECG analysis: noise cancellation and Arrhythmia detection. IEEE Trans Biomed Eng 38(8):785
Trahanias P (1993) An approach to QRS complex detection using mathematical morphology. IEEE Trans Biomed Eng 40(2):201–205
Verma AK, Saini I, Saini BS (2018) Alexander fractional differential window filter for ECG denoising. Austra Phys Eng Sci Med 41(2):519–539
Vimala K, Kalaivani V (2014) Stress causing Arrhythmia detection from ECG Signal using HMM. Inter J Innov Res Comp Commun Eng 2(5):1–7
Yakut O, Bolat ED (2018) An improved QRS complex detection method having low computational load. Biomed Signal Proc Cont 42:230–241
Yazdani S, Vesin JM (2016) Extraction of QRS fiducial points from the ECG using adaptive mathematical morphology. Digit Signal Proc 56:100–109
Yochum M, Renaud C, Jacquir S (2016) Automatic detection of P, QRS and T patterns in 12 leads ECG signal based on CWT. Biomed Signal Process Control 25:46–52
Zayed AI (1996) On the relationship between the Fourier and fractional Fourier transforms. IEEE Sig Proc Lett 3(12):310–311
Zhang C, Li X, Zhang M (2010) A novel ECG signal denoising method based on Hilbert-Huang Transform. In: 2010 International Conference on Computer and Communication Technologies in Agriculture Engineering (CCTAE), pp 284–287
Zidelmal Z, Amirou A, Adnane M, Belouchrani A (2012) QRS detection based on wavelet coefficients. Comput Methods Prog Biomed 107(3):490–496
Zidelmal Z, Amirou A, Ould-Abdeslam D, Moukadem A, Dieterlen A (2014) QRS detection using S-Transform and Shannon energy. Comput Methods Prog Biomed 116(1):1–9