ECG signal analysis using modified S-transform

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Accurate detection of QRS complexes is essential for the investigation of heart rate variability. Several transform techniques have been proposed and extensively used for the detection and analysis of QRS complexes. In this proposed work, the de-noised ECG signal is subjected to a modified S-transform for QRS complex detection.The performance analysis of the proposed work is evaluated using parameters such as sensitivity, positive predictivity and accuracy. The algorithm delivers sensitivity, positive predictivity and overall accuracy of 99.91, 99.91 and 99.77%, respectively. Furthermore, a search back mechanism is employed, which specifies the filtered electrocardiogram (ECG) segment, which was traced for the true R-peak locations. The modified S-transform based QRS complex detection algorithm provides an excellent search back range of only ±2 samples in comparison with other earlier proposed algorithms.

1. Introduction: Physical interpretation of the electrical movement of the heart is termed as electrocardiogram (ECG). It is a record of the bio-electric potentials, which commonly occurs due to polarisation and depolarisation activity of cardiac muscles acquired by placing the electrodes on the standardised locations of the skin. An ECG waveform is depicted in Fig. 1. Signal accuracy is of utmost importance for correct interpretation about heart condition. When the ECG signal is acquired, it encounters different kinds of artifacts. They are typically electrode contact noise, power line interference, motion artifacts, electromyography noise, instrumentation noise that are produced by electronic devices and so on, which have to be removed for accurate interpretation and analysis. In ECG signal, different wave sequences like P, QRS, T and U waves are interrelated with each beat. The most vital part of ECG signal processing is analysing and understanding the QRS complex waveform. In which, ‘R’-wave is a very important section of this complex and plays a pivotal role in the interpretation of heart rhythm anomalies. It also determines different relevant features of the heart.

Of late many well-known transforms have been applied for QRS complex detection. However, the recent advances in signal processing have given a new insight for analysing ECG signal called the modified S-transform, which is derived from S-transform proposed in 1996 by Stockwell [1, 2]. Recently S-transform and Shannon energy [3] based QRS complex detection has been proposed. In the proposed work, the modified S-transform is applied on filtered ECG signal to improve the presence of QRS complexes. The location of R-peak detection is carried out by setting a threshold of 30% on the maximum peak. The proposed method is validated and compared for different established parameters like positive predictivity, sensitivity and accuracy with earlier existing algorithm and it is found that it yields better results and also the search back range is only ±2 samples.

In this Letter, we present modified S-transform based QRS complex detection algorithm. The main objective of this Letter is to study the application of modified S-transform for emphasising QRS complex portions and suppressing the other local waves in the ECG signal. The proposed method consists of three major stages: noise removal using median and finite impulse response (FIR) filters, enhancement of QRS complexes using modified S-transform and peak detection using amplitude-dependent thresholding. The rest of this Letter is organised as follows. Section 2 presents the existing QRS detection algorithms. Section 3 describes the proposed modified S-transform based QRS detection algorithm. Section 4 presents the evaluation results for the standard MIT-BIH arrhythmia ECG databases. Finally, conclusions are drawn in Section 5.

2. Related works: Various QRS detection methods have been presented in literature [3–23]. Zidelmala *et al.* [3] proposed an QRS detection method using S-transform and Shannon energy. Pan and Tompkins [5] proposed a real-time QRS detection algorithm based on the digital filters and sets of amplitude-dependent, duration-dependent thresholds. The thresholds are computed using the previous peak information detected by the algorithm [5]. Hamilton and Tompkins [6] investigated the QRS detection rule using the MIT/BIH arrhythmia database. Arzeno *et al.* studied the performance of first derivative based QRS detection algorithms with different kinds of detection rules. The limitations of four methods are studied using the MIT/BIH arrhythmia database [7]. Afonso *et al.* [8] presented ECG beat detection using filter banks. Okada [9] proposed a digital filter for the QRS complex detection. The method was tested on 1085 beats of ECG of the patient (605 normal and 480 abnormal). A combined high-pass and power-line interference rejection filter with averaging over 17 samples distanced by ten samples (filter 10×17) was proposed for QRS complex detection [10]. Benitez *et al.* [11] studied the use of the Hilbert transform for detecting the QRS complexes. The QRS detection is based on the first differential of the ECG signal and its Hilbert transformed data to locate the R-wave peaks in the ECG waveform. Abibullaev and Don Seo [13] proposed a QRS detection method using wavelets and artificial neural networks. Zidelmal *et al.* [15] presented QRS detection using wavelet coefficients. A real-time QRS method was reported based on moving-averaging incorporating with wavelet de-noising [16]. The QRS detector was proposed using continuous wavelet transform (WT) [17]. The dominant rescaled wavelet coefficients was applied to magnify QRS complex and reduce the effects of other peaks. Poli *et al.* [18] proposed genetic design of optimum linear and non-linear QRS detectors. Mehta and Ligayat [19] presented comparative study of QRS detection in single lead and 12-lead ECG based on entropy and combined entropy criteria using support vector machine. Meyer *et al.* [21] presented an approach to automatically combine different QRS complex detection algorithms, here the Pan–Tompkins and wavelet algorithms, to benefit from the strengths of both methods. Lewandowski *et al.* [23] proposed a simple real-time QRS

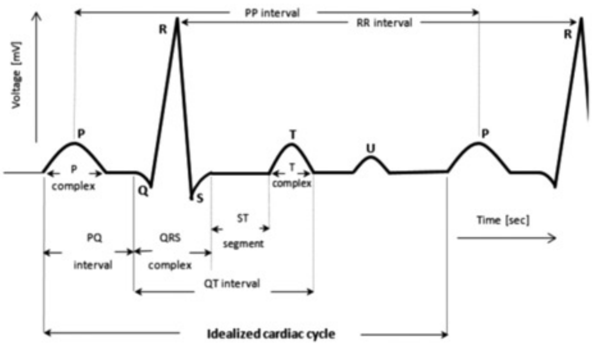

Fig. 1 *Normal ECG waveform*

detection algorithm utilising curve-length concept with combined adaptive threshold for ECG signal classification.

The standard QRS detection algorithm composed of three stages: (i) pre-processing, (ii) detection and (iii) post-processing. The main objective of signal filtering is to eliminate artifacts in pre-processing stage. In the second stage, various transformation techniques are used to generate the feature signal form the filtered signal, in which the QRS occurrence is determined by using certain peak detection logic. Finally, the decision based rules are employed for reducing the detection of false positive (FP) and false negative (FN) in the post-processing stage.Considerably good performance of these algorithms is not entirely helpful in case of noisy ECG signals. Where the detection accuracy still remains an open problem and a promising solution to these problems is under progress. R-peak detection in this Letter is carried out using modified S-transform. The performance of the proposed work was compared with other published work by using MIT-BIH arrhythmia database (MITDB).

3. Algorithm overview: Fig. 2 describes the various steps involved for the detection of R peaks in the proposed QRS algorithm.The ECG signals shall be processed in four distinct stages as in filtering, R-peak detection, true R-peak locator and parameter calculation.

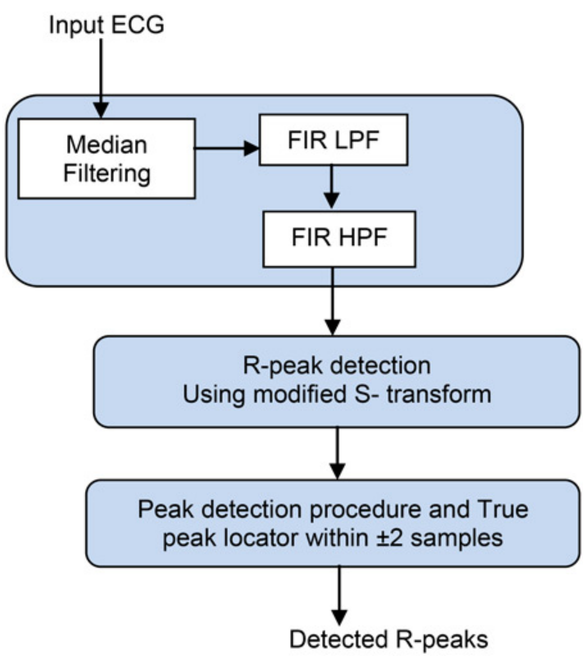

Fig. 2 *Proposed QRS complex detection algorithm*

3.1. Filtering: Most of the ECG signals available in MIT-BIH database are degraded with different artifacts like power line interference, muscle interference, composite noise and so on, on contrary to the baseline shift, which is low-frequency noise, i.e. <0.5 Hz, the power line interference is high-frequency noise above 50 Hz. Hence the initial step is to apply a median filter to the input ECG signal to remove the baseline drift using a window size of 200 ms. The median filter system function $H(z)$ is given by

$$M = \begin{cases} x\left(\dfrac{N-1}{2}\right), & N \text{ odd} \\ \dfrac{1}{2}\left[x\left(\dfrac{N}{2}\right)+x\left(\dfrac{N}{2}+1\right)\right], & N \text{ even} \end{cases} \tag{1}$$

The median filter usually depends on both past and future values for the prediction of the current point. In the next step, the presence of 60 Hz interference, muscle noise, T-wave interference and baseline wander are nullified by passing the ECG signal through a band-pass filter. The QRS energy is maximised by setting the pass band approximately to 5–15 Hz as it is a cumbersome task to design a band-pass filter directly for the desired band of 5–15 Hz. With this design specification the 3 dB pass band is achieved from about 5–12 Hz by cascading both low- and high-pass filters. This is fairly near to the design goal.

The ECG signal is normalised for eliminating and regulating both DC offset and peak levels, respectively. Fig. 3 shows the plot of ECG signal before and after filtering.

3.2. R-peak detection: The R-peak detection can be improved by using various kinds of transforms, which provides the correct location of R-peaks. Different transform techniques used in R-peak detection are as follows.

3.2.1. S-transform: The S-transform is derived from both the short-time Fourier transform (STFT) and the continuous WT. Hence, it can be realised as a frequency-dependent STFT or as a phase-corrected WT. According to Stockwell *et al.* [1], the S-transform of a continuous time series signal $u(t)$ is given by

$$S(\tau, f) = \int_{-\infty}^{+\infty} x(t) * G(t-\tau,\ f) * \exp^{-i2\pi ft}\ \mathrm{d}t \tag{2}$$

Here the window function considered is a Gaussian function given as

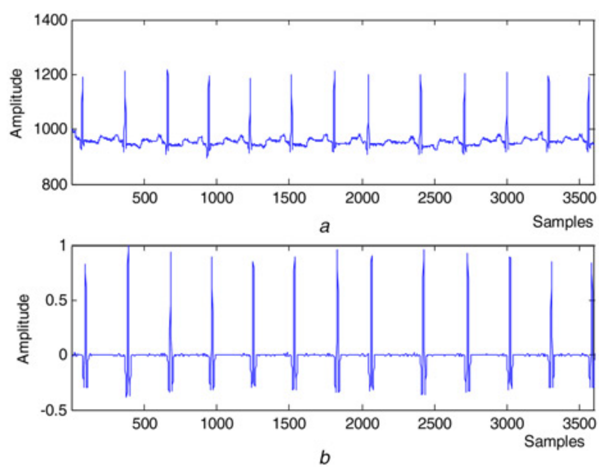

Fig. 3 *Plot of ECG signal before and after filtering*
a Input ECG signal
b ECG signal after median filtering

$$G(t,f) = \frac{|f|}{k\sqrt{2\pi}} * \exp^{-f^2 t^2/2k^2}, \quad k > 0 \tag{3}$$

In which f represents frequency, 't' and 'τ' are the time variables, 'k' is a scaling factor and is responsible for controlling the number of oscillations in the window. However, the Fourier transform of a Gaussian function is also a Gaussian; the above equation may be further written as

$$S(\tau,f) = \int_{-\infty}^{+\infty} x(\alpha+f) * e^{-2\pi^2\alpha^2/f^2} \exp^{2i\pi\alpha\tau}\, d\alpha \tag{4}$$

where the dimensions of α and frequency are same.

3.2.2. Modified S-transform: The window width σ varies inversely with frequency along with two additional positive constants termed as modified S-transform [24] which improves the position of R-peak detection with better time and frequency resolution. The S-transform for a time series $u(t)$ is defined as [1]

$$\begin{aligned} s(t,f) &= \int_{-\infty}^{+\infty} x(\tau) * G(t-\tau,f) * \exp^{-2i\pi f\tau}\, d\tau \\ &= \int_{-\infty}^{+\infty} x(\tau) * \frac{1}{\sigma(f)\sqrt{2\pi}} * \exp^{-(t-\tau)^2/2\,\sigma(f)^2} * \exp^{-2i\pi f\tau}\, d\tau \end{aligned} \tag{5}$$

The standard deviation $\sigma(f)$ in (5) is represented as follows

$$\sigma(f) = \frac{1}{|f|}$$

For the representation of the modified Gaussian window, we have selected the standard deviation $\sigma(f)$ to be

$$\sigma(f) = \frac{k}{p+q\sqrt{f}} \tag{6}$$

where p, q are positive constants, f is the signal fundamental frequency and $k \le \sqrt{p^2+q^2}$. In (5), as the chosen window $G(t,f)$ is Gaussian, the standard deviation of the earlier Gaussian function is changed in accordance with frequency to produce a new modified Gaussian window

$$G(t,f) = \frac{p+q\sqrt{|f|}}{k\sqrt{2\pi}} * \exp^{-\left(\left(p+q\sqrt{|f|}\right)^2 t^2/2k^2\right)}, \quad k > 0 \tag{7}$$

In this both 't'and 'τ' are the time variables. However both 'k' and 'q' are the scaling factors that controls the number of oscillations in the window. f is a frequency variable and p stands for a constant. It is found that the window broadens in the time domain as k value is increased; subsequently in frequency domain the frequency resolution is increased. While, by setting $q = 0$ and $k = 1$ the STFT can be obtained. As a result, the generalised S-transform with modified Gaussian window can be effectively represented as

$$S(\tau,f) = \int_{-\infty}^{\infty} X(\alpha+f) * \exp^{\left(-2\pi^2\alpha^2k^2\right)/\left(p+q\sqrt{|f|}\right)^2} * \exp^{2i\alpha\pi\tau}\, d\alpha \tag{8}$$

The S-transform of a signal in discrete form is obtained as

$$S[j,n] = \sum_{m=0}^{N-1} X[m+n] * \exp^{\left(-2\pi^2m^2k^2\right)/\left(p+q\sqrt{|f|}\right)^2} * \exp^{i(2\pi mj/N)} \tag{9}$$

Finally, the discrete Fourier transform of $x(k)$ is shifted by n in order to get $X[m+n]\cdot X(m)$ being given by

$$X[m] = \frac{1}{N} * \sum_{k=0}^{N-1} x(k) * \exp^{-j(2\pi mk/N)} \tag{10}$$

Further S-transform of signal $x(t)$ and noise $n(t)$ is

$$S(x(t)+n(t)) = S(x(t)) + S(n(t)) \tag{11}$$

From (11), it is evident that the noise can be filtered out from the S-transform with modified Gaussian window by a simple thresholding technique [25].

3.2.3. R-peak detection and correction: After extracting the QRS complex candidate signal, the amplitude-dependent threshold rule is employed for detecting the peaks. Then, the detected peaks are further processed to find true R-peak locations. The location of maximum peak within window of ±25 ms centred at the location of detected peak by the algorithm is validated for the window position with same duration in a ground-truth annotation file. Otherwise, detected peaks are considered as FPs if there are no peaks in the annotation record within the specified search window or as the FP and the FN detection.

4. Results and discussion: The S-transform with modified Gaussian window based QRS complex detection algorithm is calculated by using the MIT-BIH arrhythmia database [26]. The database contains 48 half hour length records from two channels of ECG data, which are sampled at a frequency of 360 Hz. Total 48 subjects are considered for testing.

In the simulation study, the most abnormal record 107 has been considered, as shown in Fig. 4*a*, it is an original ECG of a 63-year old man characterised by the presence of muscle noise. It is evident that the muscle artefacts are influencing the original ECG signal. Although the artefacts amplitude is higher than the R-peaks previously, it is significantly attenuated using modified S-transform as evident from the normalised frequency contour in Fig. 4*b*. Thus R-peaks are detected accurately as shown in Fig. 4*c*. Fig. 5*a* depicts multiform premature ventricular contractions (PCVs), tiny

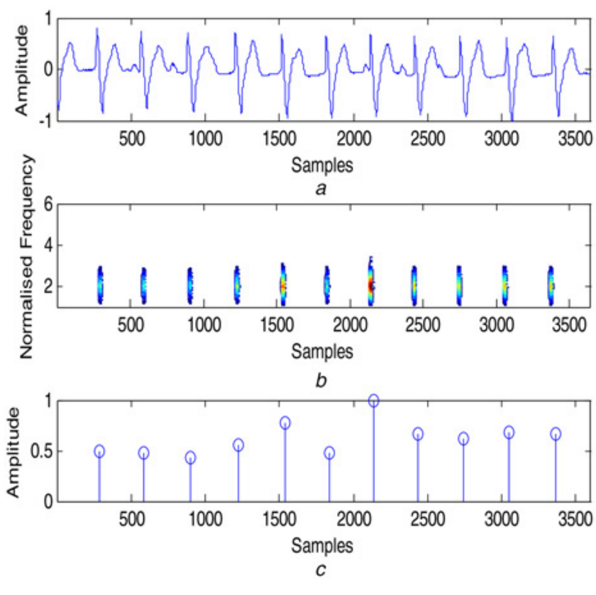

Fig. 4 *ECG waveform having segment of record 107 and detected R-peaks*
a ECG waveform having segment of record 107
b R-peak detection using modified S-transform frequency contour
c Detected R-peaks

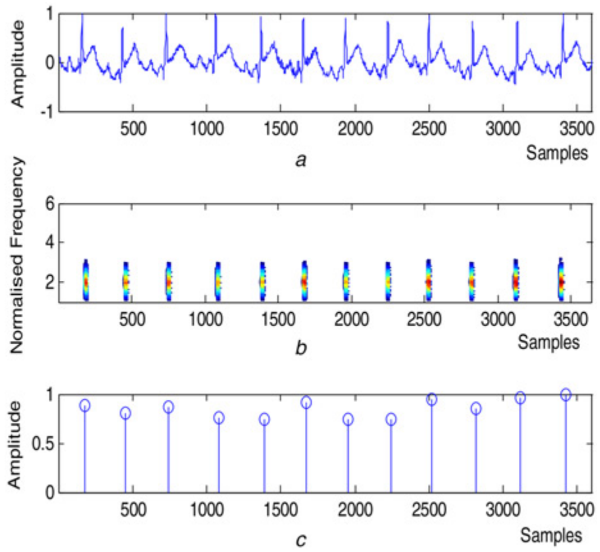

Fig. 5 *ECG waveform having segment of record 228 and detected R-peaks*
a ECG waveform having segment of record 228
b R-peak detection using modified S-transform frequency contour
c Detected R-peaks

R-waves with substantial baseline drift, for the segment of record 228 (a woman of 80 years old). The modified S-transform sharply localises and detects all the R-peaks illustrated in Figs. 5*b* and *c*, respectively. Thus, S-transform with modified Gaussian window is an effective tool for the localisation and detection of R-peaks by controlling *p*&*q* parameter. The search back range is only ±2 samples for R-peak detection.

4.1. Performance assessment: Three statistical parameters have been considered to test the performance of the QRS complex detection algorithm. The sensitivity, the positive predictivity and the accuracy are defined, respectively, as

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{12}$$

$$\text{Positive predicivity} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{13}$$

$$\text{Accuracy} = \frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN}} \tag{14}$$

where the correctly detected heart beats signify the true positive (TP). Incorrectly detected heart beats indicate FP and the undetected heart beats specify FN.

The simulation results reported in Table 1 summarises S-transform with modified Gaussian window with a total of 87 FNs, and 91 FPs. For all the annotated beats the overall sensitivity and positive predictivity are 99.91 and 99.91%, respectively. However, the overall accuracy is 99.88%. Although the Hilbert transform shows very little better sensitivity and positive predictivity as given in Table 2, but the parameters were not calculated for all the segments of ECG records as in the case for modified S-transform shown in Table 1. On the other hand, the individual ECG records detection accuracies vary from 99.32 to 100%, sensitivity vary from 99.25 to 100%, positive predictivity vary from 99.04 to 100%.

In general, any kind of problem records are illustrated by artifacts, baseline shifts and the intensity of noise. ECG segment of record 108 has abnormally tall, spiky P-waves quite unusual in morphology of usual P-waves. On account of their high slopes these P-waves are classified as QRS complexes at the beginning and end of this record. This amounts a high FP count on this record. Similarly, ECG segment of record 116 will be containing some non-QRS waves with severe unusual morphologies leading

Table 1 Experimental results of modified S-transform based R-peak detection algorithm for MIT/BIH database

Rec. no.	Total beats	TP	FP	FN	Se, %	+P, %	Acc, %
100	2273	2273	0	0	100	100	100
101	1865	1865	0	0	100	100	100
102	2187	2186	3	1	99.95	99.86	99.81
103	2084	2084	0	0	100	100	100
104	2229	2228	9	1	99.95	99.60	99.55
105	2572	2562	0	10	99.60	100	99.60
106	2027	2025	2	2	99.90	99.90	99.80
107	2137	2135	2	2	99.90	99.90	99.81
108	1763	1753	10	10	99.43	99.43	98.87
109	2532	2530	0	2	99.92	100	99.92
111	2124	2123	0	1	99.95	100	99.95
112	2539	2539	0	0	100	100	100
113	1795	1795	0	0	100	100	100
114	1879	1878	2	1	99.95	99.89	99.84
115	1953	1953	0	0	100	100	100
116	2412	2394	23	18	99.25	99.04	98.32
117	1535	1535	0	0	100	100	100
118	2278	2274	0	4	99.82	100	100
119	1987	1987	10	0	100	99.49	99.49
121	1863	1863	0	0	100	100	100
122	2476	2476	0	0	100	100	100
123	1518	1518	0	0	100	100	100
124	1619	1619	0	0	100	100	100
200	2601	2599	0	2	99.92	100	99.92
201	1963	1961	2	2	99.89	99.89	99.80
202	2136	2135	1	1	99.95	99.95	99.91
203	2980	2976	6	4	99.86	99.80	99.66
205	2656	2653	0	3	99.89	100	99.89
207	1860	1859	2	1	99.94	99.89	99.84
208	2955	2952	2	3	99.90	99.93	99.83
209	3005	3004	1	1	99.97	99.97	99.93
210	2650	2649	1	1	99.96	99.96	99.92
212	2748	2748	0	0	100	100	100
213	3251	3251	0	0	100	100	100
214	2262	2261	2	1	99.96	99.91	99.87
215	2363	2363	1	0	100	99.96	99.96
217	2208	2207	2	1	99.95	99.91	99.86
219	2154	2154	0	0	100	100	100
220	2048	2048	1	0	100	99.95	99.95
221	2427	2424	1	3	99.87	99.96	99.84
222	2483	2483	0	0	100	100	100
223	2605	2605	0	0	100	100	100
228	2053	2050	4	3	99.85	99.80	99.66
230	2256	2255	3	1	99.96	99.87	99.82
231	1571	1571	0	0	100	100	100
232	1780	1779	0	1	99.94	100	99.94
233	3079	3076	0	3	99.90	100	99.9
234	2753	2749	1	4	99.85	99.96	99.82
All	108,494	108,407	91	87	99.91	99.91	99.77

Table 2 Comparison of proposed algorithm

Sl. no.	Method	Sensitivity	Predictivity
1	the proposed method	99.91	99.91
2	Pan–Tompkins [5]	99.75	99.54
3	Hilbert transform [11]	99.94	99.93
4	curve-length transform [23]	99.86	99.84
5	S-transform [3]	99.84	99.89

Table 3 Comparison of search back range for different methods

Methods	Condition for R-peak detection	Search back range
curve-length transform	$L(n) - M(n) > S(n)$	±15 samples
Hilbert transform	based on RMS of segment	±10 samples
S-transform	30% of the maximum peak	±10 samples
modified S-transform	30% of the maximum peak	±2 samples

to FPs. However, the earlier results of other QRS detection algorithm published are compared with the proposed algorithm for R-peak detection. It is found that the proposed algorithm performs better than the existing algorithm.

Table 2 gives a comparison of proposed algorithm with earlier algorithm. Even in the presence of prominent muscular noise and base line artifacts, the proposed method shows better performance for signal affected with noise. From Table 2, it is evident that the Hilbert transform based algorithm delivers better sensitivity and positive predictivity in comparison to both Pan–Tompkins and curve-length transform based algorithm. However, the proposed modified S-transform based algorithm shows significant improvement in terms of sensitivity and positive predictivity considering all segments of ECG records than all earlier existing algorithm even better than S-transform based algorithm due to the parameter p and q.

The exact location of R-peak is precisely calculated by the search back range in a proposed ECG segment. If the search back range is low, then the algorithm is more precise in detecting the location of the R-peaks. Table 3 shows the search back range for different algorithms. For Hilbert and curve-length transform based algorithms, search back range is ±10 and ±15 samples, respectively, whereas for the modified S-transform based algorithm has the search back range of ±2 samples.

5. Conclusions: In the proposed work, a new approach of S-transform with modified Gaussian window is considered for R-peak detection and the same is demonstrated with MIT-BIH arrhythmia database. S-transform with modified Gaussian window is applied first time and is compared with several other transform along with the recently published S-transform. The statistical indices of the algorithm are higher than other earlier proposed algorithms. The QRS complex detection and localisation is exact and highly accurate with the proposed method. Primarily, the ECG signal is subjected to median and FIR filtering for noise reduction, thereby improving the results of later processing. In the second stage, the R-peaks are detected using modified S-transform which employs a scalable localising Gaussian window to detect the position of R-peaks in both time and frequency axis. Then, the locations of true R-peaks are detected by setting a threshold value of 30% of the maximum value. The proposed algorithm outperforms the earlier reported algorithms with a sensitivity of 99.91%, positive predictivity of 99.91% and an accuracy of 99.77%. In addition to this, the search back range is significantly low which is only ±2 samples than the earlier method.

6. Funding and declaration of interests: Conflict of interest: none declared.

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