Robust cardiac event change detection method for long-term healthcare monitoring applications

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A long-term continuous cardiac health monitoring system highly demands more battery power for real-time transmission of electrocardiogram (ECG) signals and increases bandwidth, treatment costs and traffic load of the diagnostic server. In this Letter, the authors present an automated low-complexity robust cardiac event change detection (CECD) method that can continuously detect specific changes in PQRST morphological patterns and heart rhythms and then enable transmission/storing of the recorded ECG signals. The proposed CECD method consists of four stages: ECG signal quality assessment, R-peak detection and beat waveform extraction, temporal and RR interval feature extraction and cardiac event change decision. The proposed method is tested and validated using both normal and abnormal ECG signals including different types of arrhythmia beats, heart rates and signal quality. Results show that the method achieves an average sensitivity of 99.76%, positive predictivity of 94.58% and overall accuracy of 94.32% in determining the changes in heartbeat waveforms of the ECG signals.

1. Introduction: Recently, mobile, wearable and/or unobtrusive wireless healthcare monitoring systems have become increasingly important to continuously monitor changes in vital signs and timely provide feedback for maintaining optimal health status of an individual anytime anywhere [1–6]. Although many light-weight and low-power wireless cardiac monitoring devices are capable of sensing, processing and communicating one or more channel electrocardiogram (ECG) signals to the decentralised and centralised diagnostic servers for screening, diagnosis and management of cardiovascular diseases, the widespread use of continuous monitoring devices have been restricted by several factors including limited battery power, bandwidth cost, diagnostic server traffic load and treatment cost [1–7]. Due to limited battery powered wireless sensors, capturing the physiological parameters or data and transmitting them continuously is not realisable for long term recording [1]. The battery-aware cross-layer time division multiple access and medium access control protocols are developed for wireless healthcare applications [2, 3]. To avoid false alarm triggered by faulty measurements, a method was developed for mobile phone to discard the faulty data and to save unnecessary transmission power [4]. An original ECG measurement system based on web-service-oriented architecture was presented to monitor health of cardiac patients and to provide emergency service [5]. In [6], a new hybrid mobile-cloud prototype was presented to enable more effective personalised medical monitoring. Although the recent communication technologies provide more bandwidth and cost effective sophisticated services, continuous cardiac monitoring device demands more power for transmission and thus reduces the battery life [7].

Many studies show that the continuous transmission of ECG signals via wired or wireless transceivers consumes a significant energy and also increases treatment cost due to the continuous utilisation of communication networks and diagnostic servers [1–6]. The traffic load of diagnostic server will be increased when a number of monitoring devices connected to the diagnostic server increases. The priority-oriented scheduling may be a solution to timely provide feedback to the subjects but it requires priority request on immediate diagnosis from a subject. The aforementioned key factors such as power consumption, bandwidth utilisation cost, diagnostic server traffic load and treatment cost can be reduced by on-device data processing but this requires a powerful low-power embedded computing platform.

The recent advances in the miniature powerful low-power embedded processors are opening new horizons in on-device data processing that are suitable for long-term continuous healthcare monitoring applications [7]. The shortcomings of the continuous wireless monitoring systems can be overcome by exploiting and exploring the morphological patterns of PQRST complexes of the ECG signals. In long-term continuous monitoring applications, the cardiac event change triggered transmission system can reduce power consumption, bandwidth cost, diagnostic server traffic load and treatment cost [7]. However, long-term cardiac health monitoring devices demand a robust automated low-complexity algorithm for accurately detecting changes in PQRST complexes and heart rhythms in the ECG signal under time-varying PQRST morphologies and various kinds of noise including baseline wanders, muscle artefacts, power-line interference (PLI) and recording instrument noise.

In this Letter, we propose an automated, reliable, low-complexity cardiac event change detection (CECD) method that can automatically detect specific changes in PQRST morphological patterns and heart rhythms, and transmit/store the recorded ECG signals whenever the cardiac event change is detected. The proposed CECD method consists four major stages: (i) signal quality assessment (SQA) for determining clinical acceptability of ECG signals; (ii) R-peak determination for extracting ECG beats and RR interval (RRI) measurement; (iii) feature extraction for obtaining the amplitude and duration of the local waves of the each of the ECG cycles; and (iv) multistage event change detection algorithm. The rest of this Letter is organised as follows. Section 2 presents the signal processing techniques that are used for implementation of the proposed CECD method. In Section 3, we test and validate the effectiveness of the proposed CECD method using a wide variety of ECG signals taken from the well-known four MIT-BIH ECG databases. Finally, conclusions are drawn in Section 4.

2. Methods and materials: In this Letter, we mainly focus on design and development of automated, reliable and low-complexity signal quality-aware CECD method that can automatically detect specific changes in PQRST morphological patterns and heart rhythms, and transmit/store the recorded ECG signals whenever the cardiac event change is detected. In this Letter, the CECD is implemented using the significant clinical features including RRI, amplitude, polarity and duration of the P-wave, QRS-complex, and

T-wave and beat-to-beat similarity index. The proposed CECD method that consists of following stages include the SQA, R-peak determination and beat extraction, ECG feature extraction and multistage CECD rules. In the next subsection, we describe the signal processing techniques that are used for implementing the robust low-complexity cardiac event detection method.

2.1. ECG signal quality assessment: In real-time ECG recording conditions, the ECG signals are corrupted with different types of noise including baseline wanders, muscle artefacts, PLI and instrumentation noise. Thus, assessment of the ECG signal quality is the most important preprocessing step in unsupervised telehealth and intensive care applications to reduce a number of false alarms. Therefore, in the first stage, we implement the ECG SQA for determining clinical acceptability of the recorded ECG signals. The proposed method further processes the ECG signals in the second stage if the ECG quality is good otherwise the ECG signal is discarded.

In most intensive care unit and unsupervised telehealth applications, the input ECG signal is classified into two groups: acceptable ('good') and unacceptable ('bad'). The unacceptable signal quality class includes noisy ECG signals that often corrupted with severe baseline wanders, muscle artefacts, PLI and instrumentation noises which can mask important features of the local waves of ECG signals. The baseline wanders can be caused by respiration, changes in electrode impedance and motion which distorts the ST segment. The presence of severe baseline wanders and muscle artefacts can distort the morphological features of the local waves such as P-wave, QRS-complex, T-wave and U-wave. Thus, reliable and accurate determination of essential clinical features such as amplitude, duration and shape of the local waves is more difficult [8]. The severity of the noise is quantified by measuring the amplitude, duration, zero-crossings (ZCs) and local maxima and minima from the low-frequency (LF) and high-frequency (HF) components extracted from the ECG signal.

In this Letter, the proposed ECG SQA method consists of three major steps: (i) moving average (MA) filters for extracting the LF and HF components; (ii) the time-domain feature extraction for measuring the amplitude, duration, ZCs and local maxima and minima; and (iii) decision rule for classifying the input ECG signal into acceptable ('good') and unacceptable ('bad'). The noise-amplitude thresholds are chosen based on the clinically acceptable amplitudes of the smallest local waves in the ECG signals. The algorithm for assessing the ECG signal quality is summarised as follows:

Step 0: Read the recorded ECG signal

Step 1: Extract the baseline wander from the ECG signal using a higher-order MA filter. The length of MA filter is empirically chosen such that it can adequately capture a baseline wander with frequency below 1 Hz. For detecting the presence of baseline wanders, the maximum absolute amplitude (MAA) of $b[n]$ is compared with the predefined amplitude threshold of 0.1 mV which is the acceptable level of baseline wanders [9, 10]. The severity of the baseline wanders is quantified by measuring a total number of local maxima and minima (N_{lm}) that are greater than the magnitude of 0.1 mV. If the N_{lm} is greater than a predefined value of 5 for each 10 s duration ECG signal then the input signal is classified as unacceptable for further processing.

Step 2: Extract the HF noises including muscle artefacts, power-line and instrumentation noises from the ECG signal using the MA filter implemented as

$$v[n] = \frac{1}{M+1} \sum_{k=0}^M x[n-k] \quad (1)$$

$$h[n] = x[n] - v[n], \quad n = 0, 1, 2, \dots, N-1. \quad (2)$$

where M denotes the length of the MA filter that is chosen such that it can adequately capture the signal components with frequencies below 40 Hz. Since the HF signal $h[n]$ includes the HF portions of the QRS complexes, the HF signal is divided into blocks with duration of 50 ms with shift of one sample and then a number of ZCs is computed for discriminating the QRS complex portions from the noise portions. The overlapping blocking process is implemented as

$$v_k[n] = v[k+n], \quad n = 1, 2, \dots, P \quad (3)$$

where $k=0, 1, \dots, N-1$. $v_k[n]$ is the k th block and P denotes the size of the block. For each of the blocks of the ECG signals, a number of ZCs are computed as

$$Z[k] = \begin{cases} \text{Compute } ZC_k & \text{if } \max_k > 0.02 \\ \text{Assign } 0 & \text{otherwise} \end{cases} \quad (4)$$

where $\max_k$ is the MAA of k th block and the ZC denotes the number of ZCs which is computed as

$$ZC_k[m] = \frac{1}{2} \sum_{n=1}^{N-1} |\text{sgn}(v_k[n]) - \text{sgn}(v_k[n-1])|, \quad (5)$$

From the experimental results, it is observed that the number of ZCs for the HF noise block is much higher than the number of ZCs for the QRS complex block. In this Letter, the ZC feature with duration threshold of 300 ms is used for characterising the HF noise segments from the localised QRS complex segments. Then, the severity of HF noise including the muscle artefacts and PLI in the input ECG signal is determined by comparing the MAA of each block with a predefined value of 0.2 mV. If amplitude and duration criteria are satisfied then the input ECG signal is classified as unacceptable for further processing.

Step 3: Send the ECG signal which satisfies as acceptable quality criteria for further processing.

The effectiveness of the SQA approach is tested using both clean and noisy ECG signals. The results of the SQA approach are shown in Figs. 1 and 2 for the ECG signals corrupted with baseline wanders and muscle artefacts, respectively. The feature envelopes as shown in Figs. 1e, f and 2e, f clearly show that the ZC feature with duration threshold can be capable of discriminating the muscle artefacts (as shown in Fig. 2e) from HF portions of QRS complex portions (as shown in Fig. 1e) in the extracted HF signal. The duration threshold of 300 ms is chosen based on the refractory period of cardiac muscle. The SQA results demonstrate that the proposed features such as number of local minima and maxima, MAA, ZCs and duration threshold are capable of significantly detecting the presence of baseline wanders and muscle artefacts in the ECG signal. The detection performance of the SQA is further evaluated using wide variety of clean and noisy ECG signals in Section 3.

2.2. R-peak determination and ECG beat extraction: In this subsection, we present a robust low-complexity straightforward R-peak detection algorithm without using the search-back mechanism with sets of detection thresholds and learning phase unlike other existing R-peak detection algorithms. The R-peak detection algorithm consists of Gaussian derivative filter, adaptive amplitude thresholding, Shannon energy envelope extraction and first order Gaussian difference-based peak finding logic [11]. The pseudo code for the R-peak detection is summarised in Algorithm 1 (see Fig. 3). On the basis of the time-instants of past and present R-peaks, the beat waveforms are extracted from the ECG signal.

Fig. 1 Illustrates the results of the proposed SQA approach for the ECG signal corrupted with baseline wander
a Original ECG signal
b Extracted baseline wander component
c Detection result of baseline wander
d Extracted HF component from the original ECG signal
e Zero-crossing envelope
f Detection result of muscle artefacts

The pseudo code for the proposed ECG beat extraction is illustrated in Algorithm 1 (see Fig. 3), which consists of following steps: left shifting, peak aligning, period and amplitude normalisation and peak centring. The results of the ECG beat extraction algorithm are shown in Fig. 4 for the ECG signals including different PQRS morphological patterns. For each of successive two ECG beats, the morphological features are computed in determining the changes in cardiac beat patterns.

2.2.1 Cardiac event change detection: Literature studies show that the continuous transmission of ECG signals consumes a significant energy and increases the bandwidth utilisation cost, traffic load of diagnostic server and treatment cost [12]. In most normal and chronic subjects, the recorded ECG signals exhibit the presence of similar PQRS morphological patterns in long-term ECG recordings. Even in the cases of pathological condition, there is a significant inter-beat correlation for a shorter duration. Therefore, we attempt to reduce power consumption, diagnostic server traffic load, bandwidth utilisation and treatment costs by transmitting only the ECG signals that exhibit specific changes in heartbeats [7].

The ECG signals are generally grouped into normal and abnormal classes based on the RRI variation and amplitude, duration and shape features of the local waves such as P-wave, QRS complex and T-wave of the ECG signal. The QRS-width, the positive and negative amplitudes of the QRS complex and shape of the QRS complex are the most predominant features that are widely used for discrimination of different types of arrhythmia. Most cardiovascular diseases impact

Fig. 2 Illustrates the results of the proposed SQA approach for the ECG signal corrupted with muscle artefacts
a Original ECG signal
b Extracted baseline wander component
c Detection result of baseline wander
d Extracted HF component from the original ECG signal
e Zero-crossing envelope
f Detection result of muscle artefacts

changes in RRIs and morphological features including the amplitude, duration and shape of heartbeats that are widely used by the physicians to interpret whether heartbeat belongs to the normal sinus rhythms or to the appropriate classes of arrhythmia [13]. For detecting the specific changes in the acquired ECG signals, the predominant features such as RRI, duration, amplitude and shape of the PQRS morphological patterns are extracted. In this Letter, the CECD is implemented using the following decision rules:

Rule 01 – RR interval variation: The RRI (variation of beat-to-beat interval) plays a major role in evaluation of changes in the heart rate variability in patients with obstructive sleep apnea syndrome (OSAS) and in assessing the autonomic nervous system functions. The RRI can quantify the prematurity of the heartbeat [10, 14]. Thus, the RRI feature is used as one of the features for determining a change of cardiac events in the recorded ECG signal. In this Letter, a change of cardiac event is detected if RRI ratio $RRIR = (\min(RRI_i, RRI_{i-1}) / \max(RRI_i, RRI_{i-1}))$ is less than a predefined acceptable RRIR threshold of 0.9.

Rule 02 – QRS amplitude variation: In clinical studies, the effect of the QRS amplitude was investigated in diagnosing patients with dilated cardiomyopathy, hypercalcemia, pericardial effusion, myocardial loss, left ventricular hypertrophy, emphysema, sepsis, acute haemorrhage, severe dehydration and hypovolaemia, obesity and changes in ventricular internal dimensions [10]. The studies show that the perturbations in the amplitude of QRS complexes are apparent in analysis of cardiovascular diseases [15]. In this Letter, a change in R-wave amplitude (R_{amp}) is detected if $|R_{amp(i)} - R_{amp(i-1)}| > 25\% \min(R_{amp(i)}, R_{amp(i-1)})$.

Algorithm 1

Function: [Rpeak, ECGBeat] = RpeakECGbeatExtraction(x,Fs)

Input: x[k] := ECG signal ; $k = 1, 2, \dots, N_1$

Output: Rpeaks[n] := position of Rpeaks in ECG signal

Procedure:

Step 0: Perform band pass filtering using Gaussian window and calculate first order difference

$$\mathbf{h}[k] = \mathbf{G}[k] - \mathbf{G}[k-1]; \mathbf{G} = e^{-\frac{1}{2} \left(\frac{2\epsilon L}{L} \right)^2}$$

$\mathbf{yy}[k] := \text{filtfilt}(h, 1, xx);$ //perform zero phase filtering

$\mathbf{d}[k] := \mathbf{yy}[k+1] - \mathbf{yy}[k]$

Step 2: Apply adaptive thresholding, $\bar{\mathbf{d}}[n] = (|\mathbf{d}[n]|^2 > \sigma_d) \cdot (\mathbf{d}[n])^2$
 σ_d represents the standard deviation of $\mathbf{d}[n]$.

Step 3: Compute Shannon energy and smoothing process,

$SE = -\bar{\mathbf{d}}[n] * \log \bar{\mathbf{d}}[n]; \mathbf{s}[n] = \text{filtfilt}(\mathbf{b}, \mathbf{a}, SE)$

$\mathbf{b} = \text{ones}(1, WS)/WS$; and $\mathbf{a} = 1$; $WS = \text{floor}(2.5 * Fs)$

Step 4: Peak finding logic using Gaussian derivative operator

$\mathbf{z}[n] = \text{conv}(\mathbf{s}, \mathbf{h});$ //convolution of $\mathbf{s}[k]$ and $\mathbf{h}[k]$

$\mathbf{r} = (\text{sign}(\mathbf{z}[n]) > 0) \&\& (\text{sign}(\mathbf{z}[n+1]) < 0);$

// store locations of negative zero-crossing points in $\mathbf{z}[n]$

Step 5: R Peak location adjustment

$sw = \text{floor}(0.05 * Fs);$ // window size to search true R-peaks

for k=1 to length($\mathbf{r}$) **do**

$\text{[Rpeak]} = \max\{\mathbf{x}[\mathbf{r}(k) - sw : \mathbf{r}(k) + sw]\}$ //store current locations

endfor

Step 5: ECG Beat Extraction

for i= 1 to K-1;

Read ECGbeat: $s1[m] = s[r[i] : r[i+1]]$; $m = 1, 2, \dots, M$,

Left shifting: $s2[m] = s1[r[i] - nshift : r[i+1] - nshift]$,

Peak aligning by circular shifting: $s3[m] = \tilde{s2}[m - nshift - 1]_M$,

where $\tilde{s2}[m]_M$ is considered as a circular sequence of length M,

Perform period normalisation: $s4[l] = \text{interpft}(s3, L)$, //interpolation in FFT domain [12]

Perform amplitude normalisation: $s5[m] = s4[m] / |\max(s4[m])|$,

Perform peak centering: $s6[m] = \text{fftshift}(s5[m])$,

Construct ECG beat matrix: $\mathbf{b}[i,:]= s6[m]$,

End.

end procedure:

Fig. 3 R-peak detection and beat extraction algorithm

Fig. 4 Illustrates the results of the ECG beat extraction algorithm

Table 1 Performance of the proposed method for the ECG signals taken from the four well-known ECG databases

Record	R-peak detector			SQA			Cardiac event detection					
	Se, %	PP, %	OA, %	Se, %	PP, %	OA, %	TP	FN	FP	Se, %	PP, %	OA, %
100	100	100	100	99.87	99.19	99.01	16	0	3	100	84.21	84.21
101	100	100	100	99.34	99.76	98.94	0	0	0	100	100	100
102	100	100	100	98.04	98.95	96.19	87	8	0	91.58	100	91.58
103	100	100	100	97.99	97.58	96.52	0	0	0	100	100	100
104	100	100	100	92.15	90.47	87.75	102	0	0	100	100	100
105	100	100	100	99.39	97.73	95.05	11	0	0	100	100	100
106	100	100	100	96.13	97.46	95.13	107	0	0	100	100	100
108	100	100	100	87.35	90.68	85.64	19	1	0	95	100	95
109	100	100	100	95.55	93	91.85	40	0	1	100	97.56	97.56
113	100	100	100	95	93.78	91.61	125	0	4	100	96.90	96.90
118	100	100	100	91.68	90.33	89.34	106	0	2	100	98.15	98.15
121	100	100	100	90.11	89.39	88.91	89	1	2	98.89	97.80	96.74
123	100	100	100	95.25	92.36	90.55	78	0	3	100	96.30	96.30
124	100	100	100	94.12	93.67	92.34	9	0	0	100	100	100
200	100	100	100	93.45	94.11	91.83	11	0	0	100	100	100
201	99.98	100	99.98	91.76	92.61	90.93	117	2	4	98.32	96.69	95.12
208	99.97	100	99.97	92.97	91.65	88.89	103	4	2	96.26	98.10	94.50
212	100	100	100	94.12	93.63	92.89	41	0	0	100	100	100
214	100	100	100	91.32	92.64	90.56	89	0	2	100	97.80	97.80
219	100	100	100	95.91	95.32	94.86	37	0	0	100	100	100
222	100	100	100	94.33	93.72	93.07	84	1	2	98.82	97.67	96.55
228	99.97	99.76	99.87	90.07	89.65	88.93	86	2	6	97.73	93.48	91.49
230	100	100	100	95.61	94.34	93.88	113	0	2	100	98.26	98.26
231	100	100	100	96.65	96.06	95.97	36	0	3	100	92.31	92.31
total	100	100	100	94.51	94.09	92.53	1506	19	36	99.02	97.72	96.77
MIT-BIH polysmnographic database												
slp01am	100	100	100	99.15	100	99.15	0	0	1	100	99	99
slp02am	100	100	100	99.04	99.87	97.23	101	0	0	100	100	100
slp02bm	100	100	100	98.11	97.37	95.29	61	0	0	100	100	100
slp03m	100	100	100	98.32	96.37	94.91	25	0	4	100	86.21	85.20
slp14m	100	100	100	97.33	95.81	93.38	14	0	0	100	100	100
slp32m	100	100	100	98.66	97.53	96.93	0	0	1	100	99	99
slp45m	100	100	100	97.24	96.56	94.12	0	0	0	100	100	100
slp48m	100	100	100	96.54	97.55	95.18	18	0	2	100	90	90
slp66m	100	100	100	94.94	95.21	92.86	0	0	0	100	100	100
slp67xm	100	100	100	95.36	94.65	92.95	3	0	0	100	100	100
total	100	100	100	97.47	97.09	95.20	222	0	8	100	97.42	97.32
MIT-BIH atrial fibrillation database												
04043m	100	100	100	98.28	97.65	96.16	0	0	1	100	99	99
04048m	100	100	100	97.53	98.85	96.44	5	0	4	100	55.56	55.56
05091m	100	100	100	94.5	93.22	92.95	0	0	1	100	99	99
05261m	100	100	100	97.54	96.31	94.89	15	0	0	100	100	100
06995m	100	100	100	97.79	95.81	93.38	100	0	0	100	100	100
04908m	100	100	100	98.73	96.56	94.12	92	0	8	100	92	92
05121m	100	100	100	97.69	97.55	96.61	71	0	4	100	94.67	94.67
04936m	100	100	100	96.74	94.29	92.98	99	0	0	100	100	100
06426m	100	100	100	96.28	97.12	94.38	78	0	2	100	97.5	97.5
06453m	100	100	100	96.74	98.94	95.17	95	0	1	100	98.96	98.96
total	100	100	100	97.18	96.64	94.71	555	0	21	100	93.67	93.67
MIT-BIH ST change database												
304m	100	100	100	98.64	96.65	94.34	0	0	0	100	100	100
310m	100	100	100	97.54	97.31	96.19	0	0	0	100	100	100
319m	100	100	100	96.29	97.19	94.38	2	0	2	100	50	50
320m	100	100	100	98.91	96.85	94.89	16	0	2	100	88.89	88.89
321m	100	100	100	95.89	96.04	95.35	0	0	1	100	99	99
322m	100	100	100	98.74	96.56	94.12	25	0	3	100	89.29	89.29
323m	100	100	100	98.61	97.68	96.12	32	0	4	100	88.89	88.89
325m	100	100	100	96.75	96.94	95.97	0	0	0	100	100	100
total	100	100	100	97.67	96.90	95.17	75	0	12	100	89.51	89.51
average	100	100	100	96.70	96.18	94.41	2358	19	77	99.76	94.58	94.32

Fig. 5 Illustrates the different features extracted for the proposed cardiac event change detector
a Irregular rhythm having R–R variation in record no. 100 of MIT-BIH arrhythmia database
b Sudden change in shape of ECG beat for record no. 208 of MIT-BIH arrhythmia database
c Amplitude variation in R-peak of ECG beat in record no. slp02am of MIT-BIH polysomnographic database

Rule 03 – QRS width variation: The duration of QRS complex is used for determining ventricular dysfunctions. The duration of the QRS complex is normally 0.06–0.1 s [14, 16]. The relatively short duration QRS complex indicates that ventricular depolarisation normally occurs very rapidly. If the QRS complex is prolonged (>0.12 s), conduction is impaired within the ventricles. The widened QRS complexes are caused due to the right bundle branch block (RBBB) or left BBB (LBBB), hyperkalemia, and Wolf-Parkinson-White patterns. In this Letter, a change of cardiac event due to the variation of QRS complex duration (QRS_{dur}) is detected by considering the 10% variation of the past QRS duration. A change of cardiac event is detected if $|QRS_{dur(i)} - QRS_{dur(i-1)}| > 10\% \min(QRS_{dur(i)}, QRS_{dur(i-1)})$.

Rule 04 – ECG beat waveform shape variation: The shapes of the local components such as P-wave, QRS-complex, T-wave, and ST-segment may vary due to cardiac conduction diseases related to anatomical abnormalities of the heart and/or the specialised conduction system. In many ECG arrhythmia recognition systems, the waveform shape is used as specific feature for classification of ECG beats (including, normal, atrial premature, paced, premature ventricular, LBBB and RBBB) [15]. In this Letter, a waveform similarity index (WSI) is used for determining changes in cardiac events due to the shape variations in heartbeats in the ECG signal. The WSI between two successive beat waveforms is computed as

$$\Gamma = \frac{\sum_{i=1}^N [x_i(k) - \mu_{01}] \sum_{i=1}^N [x_{i-1}(k) - \mu_{02}]}{\sqrt{\sum_{i=1}^N [x_i(k) - \mu_{01}]^2} \sqrt{\sum_{i=1}^N [x_{i-1}(k) - \mu_{02}]^2}}, \quad (6)$$

where Γ denotes the WSI and μ_{01} and μ_{02} are the mean values of the ECG beat waveforms x_i and x_{i-1} , respectively. A change in ECG beats due to the shape variations is detected by comparing Γ with the predefined similarity threshold of 0.9, which is used in the previously published ECG beat similarity matching techniques [17, 18].

Fig. 6 Illustrates the detected individual events (marked by red line) for the ECG signals taken from the MIT-BIH arrhythmia database
a Normal ECG signal portion taken from record 100 of MIT-BIH arrhythmia database
b Event detected due to the RRI variation for the ECG signal taken from record 100
c Event detected due to the changes in shape of heartbeat waveforms of the ECG signal taken from record 200
d Event detected due to amplitude variation in ECG beat waveform in record 102
e Event detected for noisy ECG signal corrupted with muscle artefacts

3. Results and discussion: In this section, the performance of each stages of the proposed CECD is evaluated using a wide variety of ECG signals and standard benchmark parameters.

3.1. Test ECG databases and performance metrics: The proposed method is tested and validated using different kinds of ECG signals taken from the well-known ECG databases including MIT-BIH arrhythmia database, MIT-BIH polysomnographic database, MIT-BIH atrial database and MIT-BIH ST change database. These databases contain different types of PQRST morphological patterns and various kinds of artefacts and noise including baseline wanders, PLI and muscle artefacts. The ECG signals are digitised with different sampling rates and sample amplitude resolutions. In the proposed method, the ECG SQA is first performed for determining clinical acceptability of the recorded ECG signals. In the second stage, R-peak determination and ECG beat waveform extraction are performed as illustrated in Algorithm 1 (see Fig. 3). In the third stage, the RRI and ECG waveform features including amplitude, duration and shape are extracted from each of the ECG beat waveforms for determining the similarity between two consecutive ECG beat waveforms. The effectiveness of the proposed SQA, R-peak determination and CECD algorithms are validated using standard benchmark parameters such as sensitivity (Se), positive predictivity (PP) and overall accuracy (OA), that are defined as

$$Se = \frac{TP}{TP + FN}, PP = \frac{TP}{TP + FP}, OA = \frac{TP}{TP + FN + FP} \quad (7)$$

Table 2 Comparative analysis results with existing method

	[7]	Proposed method
Se, %	99.11	99.77
PP, %	93.64	94.48
(OA), %	93.37	94.23
SQA	no	yes
computational time	2.24 s	0.6 s

where TP denotes the true positives, FP denotes the false positives and FN denotes the false negatives.

The ECG recordings from the MIT-BIH arrhythmia database were digitised at 360 samples per second per channel with 11 bit resolution over a 10 mV range. The MIT-BIH arrhythmia database includes different types of arrhythmias with regular and irregular rhythms and various kinds of artefacts and noise [19]. The MIT-BIH polysomnographic database is a collection of recordings of multiple physiologic signals during chronic OSAS [19]. These physiological signals were digitised at a sampling interval of 250 Hz and 12 bits/sample. The MIT-BIH atrial fibrillation database contains long-term ECG recordings of human subjects with atrial fibrillation that are sampled at 250 samples per second with 12 bit resolution over a range of 10 mV range [19]. The MIT-BIH ST change database is used for evaluation of algorithms for analysis of ST and T-wave changes. The database contains two signals, each sampled at 250 samples per second with 12 bit resolution over a nominal 20 mV range.

For validation purposes, each record from the test ECG databases is visualised to manually annotate changes in RRI, amplitude and duration of the QRS complexes, beat waveform shape and signal quality. A total of 8200 cardiac segments and 5842 normal segments (no event) are used for evaluating the proposed method. The beat changes in each of the cardiac cycles are identified in ECG recordings taken from all the test ECG databases. The annotations of each cardiac cycle were compared with CECD results obtained using the proposed method. For all four ECG databases, the detection performances of the proposed SQA, R-peak determination and cardiac event detection algorithms are summarised in Table 1. The R-peak detection results show that the proposed straightforward detection algorithm achieves an Se of 100% and PP of 100% for most test ECG signals except the ECG signal taken from records 201, 208 and 228 of MIT-BIH arrhythmia database (see record 208 in Fig. 5b). The advantages of the proposed algorithm are that it does not use search back mechanism with

multiple amplitude and duration dependent thresholds and learning phase unlike other existing R-peak detection algorithms. The results further show that the algorithm is capable of determining R-peak instants in the ECG signals including different PQRS morphologies with (i) wide QRS complexes, (ii) negative QRS polarities, (iii) low-amplitude QRS complexes, (iv) sudden changes in QRS morphologies, (v) sudden changes in RRIs, (vi) sudden changes in QRS amplitudes and (vii) sharp P- and T-waves.

In long-term continuous ECG monitoring applications, the ECG signals may be corrupted with various kinds of artefacts and noise including baseline wanders, muscle artefacts, PLI and instrumentation noises under both resting and ambulatory recording conditions. The major key challenges such as transmission power, bandwidth utilisation cost and server traffic load can be reduced by determining clinical acceptability of ECG signals before processing and transmitting the recorded ECG signals to the remote diagnostic centre. Therefore, this Letter attempts to develop an automated low-complexity (SQA) approach for determining clinical acceptability of ECG signals. The SQA approach classifies the input ECG signal into two groups: acceptable ('good') and unacceptable ('bad'). The unacceptable signal quality class includes noisy ECG signals corrupted with severe baseline wanders, muscle artefacts, PLI and instrumentation noise.

The SQA results are summarised in Table 1 for the ECG signals taken from four ECG databases. From the results, it is observed that the SQA approach has an Se of 87.35–99.87%, a PP of 89.39–100% and an OA of 85.64–99.0% for test ECG signals. By visualising the SQA results for each of the test ECG signals, it has been found that there was a confusion in grading the quality of the ECG signals which is corrupted with low-amplitude baseline wanders, muscle artefacts and instrumentation noise. Therefore, the SQA approach has a detection rate from 85 to 95% for most test ECG signals. After cross-validation of SQA results, it is noted that the amplitude thresholding on the extracted baseline wanders and high frequency noises can provide promising results after re-examining the manual annotations based on the magnitude of the extracted baseline wanders and HF noises. However, in this Letter, we report the SQA results obtained for the original signal quality annotations. Fig. 6 illustrates the effectiveness of the proposed CECD method for five types of ECG signal including different PQRS morphological patterns, heart rate variation and signal quality.

Table 1 summarises the results of the proposed CECD method for test ECG signals taken from four well-known ECG databases. From the detection results, the proposed method achieves an Se of 100% for most of the test ECG signals taken from the

Fig. 7 Automated ECG event detector and notification application developed on android platform version Lollipop 5.0, 1.2 GHz quad-core Qualcomm Snapdragon 410 MSM8916 processor and 2 GB of RAM

MIT-BIH arrhythmia database. Experimental results show that the method detects all cardiac event change segments in the ECG signals that were annotated in the test ECG records. The method has a PP of 100%, 95–99%, 84–95% and 50–55% for the numbers of test ECG recordings of 23, 17, 10 and 2, respectively. The method has correct event change detection rate of 100% meanwhile the method has false detection rate of 98.64% for total number of 8200 cardiac segments. Experimental results demonstrate that the method does not miss any cardiac event change segments but has false detection of 77 cardiac segments as event change segments out of total number of 5842 normal cardiac segments. Comparative analysis results as shown in Table 2 demonstrate that the proposed method outperforms existing event detection method [7] both in terms of performance parameters and computational time.

The proposed CECD algorithm is first developed on MATLAB and then implemented on android phone to study the feasibility of the proposed algorithm for real-time mobile healthcare monitoring applications. The developed android application for the proposed algorithm is shown in Fig. 7. The proposed CECD algorithm has computational time of 100 ms in processing the 10 s ECG signal. Experiment results show that the real-time transmission of 15 min normal ECG signal results in 10% battery power consumption. Results further show that the power consumption of 40% is saved by integrating the proposed CECD algorithm with real-time health monitoring system.

4. Conclusion: In this Letter, we present an automated robust CECD method for resource-energy efficient telehealthcare monitoring applications. The proposed method consists of the following stages: SQA, R-peak determination and ECG beat extraction, event change feature extraction and CECD rules. The proposed method is tested and validated using a wide variety of ECG signals including different arrhythmia beats, heart rates and signal quality that are taken from the four well-known ECG databases. The proposed method achieves an average Se of 99.76%, PP of 94.58% and OA of 94.32% in determining the changes in cardiac heartbeat waveforms in the ECG signals. Experimental results show that the method has a great potential in reducing the transmission power, bandwidth utilisation cost and diagnostic server traffic load under remote healthcare monitoring applications.

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