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An Open-Access ECG Database for Algorithm Evaluation of QRS Detection and Heart Rate Estimation

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R-peak detection for dynamic electrocardiogram (ECG) signal is still a challenge due to the poor signal quality, which leads to inefficient recognition of the existing R-peak detection technologies. Collected in clinical environment, ECG signals from current widely-used open-access ECG databases are basically provided with high quality. Many methods can achieve high recognition rate on these databases but fail to work properly if the signal quality reduces. This study presents an open-access ECG database comprises of challenging QRS segments. The database is used for the 2nd China Physiological Signal Challenge (CPSC 2019), where participants are expected to identify QRS locations and then estimate HR from these episodes. All the approved algorithms are evaluated by scoring standards and regulations defined in terms of both R-peak detection and HR estimation, with Pan & Tompkin (P&T) algorithm as a benchmark.

Keywords: Electrocardiogram (ECG), QRS Detection, Heart Rate (HR), Database, CPSC.

1. INTRODUCTION

Electrocardiogram (ECG) signal plays an important role in non-invasively monitoring and clinical diagnosis for cardiovascular disease (CVD) [1]. Detection of QRS complex is an essential step for ECG signal processing, and can benefit the following heart rate (HR) calculation and abnormal situation analysis. Since it reflects the electrical activity within the heart during the ventricular contraction, the time of its occurrence as well as its shape provide much information about the current state of the heart [2, 3]. QRS detection generally involves linear and non-linear transformations of raw ECG to enhance the QRS complexes, and can be achieved by techniques that focus on the ECG amplitude, its first and second derivatives [4, 5], or by using digital filters [6]. HR is a sensitive indicator of the cardiovascular system load and estimation of instantaneous HR is one of the most important problem in physiological measurement. HR is usually estimated from the detected QRS locations, but sometime it can be directly estimated from the ECG waveforms without any feature detection (like QRS complex, P wave) [7, 8].

Although QRS detection methods have been severely tracked throughout the last several decades and many sophisticated methods have been proposed for HR estimation [6, 9], accurate QRS location and HR estimation are still challenging in noisy signal episode or abnormal rhythm waveforms, especially when the ECG recordings are from dynamic ECG Holter or wearable ECG devices [6, 10–13]. It is true that many of the developed QRS detection algorithms can achieve high accuracy (over 99% in sensitivity and positive predictivity) when tested over the standard ECG databases such as MIT-BIH Arrhythmia Database or AHA Database [14, 15]. However, these algorithms may fail when used in the dynamic environment that includes severe noises [16]. A recent study confirmed that none of the common QRS algorithms can obtain over 80% detection accuracy when tested on the dynamic noisy ECG database [17, 18]. Moreover, even tested on some open-access dynamic ECGs, ECG episodes with good signal quality account for a majority and thus the evaluation results usually hide the failure of QRS detectors in case of noisy or pathological signals. In addition, ECG morphology has significant individual variability in patients of various arrhythmias, such as premature arrhythmia, ventricular arrhythmia, and conduction arrhythmia [19]. So QRS detection should be immune to physiological variability of ECG waveforms and HR rhythms [20].

Well-thought-out databases can essentially improve the progress of related technologies, and the usefulness has been verified by some widely used open-access databases, such as the developed ECG database [21], heart sound database [22],

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electroencephalogram (EEG) database [23], 1st CPSC [24] etc. Thus, a well-designed dynamic ECG database that can adequately test the performance of QRS detection and HR estimation algorithms is highly needed. This study presents a new designed ECG database containing only challenging ECG episodes for QRS detection and HR estimation. The challenging situations incudes pathological arrythmias, extreme sinus tachycardia or sinus bradycardia, poor signal quality due to the artifacts and noises, waveform morphological variability, etc., aiming to encourage participants to develop more efficient and robust algorithms for QRS detection and HR estimation. In addition, it is worth to note that, although HR can be calculated from the detection results of QRS complexes, it can be still estimated without QRS detection step [7, 8].

2. CHALLENGE DATA

Training data consists of 2,000 single-lead ECG recordings collected from patients with CVD. Each of the recording last for 10 s. Test set contains the similar ECG recordings with the same time lengths, but it is unavailable to public and will remain private for the purpose of scoring for the duration of the Challenge and for some period afterwards. ECG recordings were obtained from multiple sources, although in all cases they are presented as 500 Hz sample rate here. All recordings were provided in MATLAB format (each including two .mat file: one is ECG data and another one is the corresponding QRS annotation file). Pan & Tompkins (P&T) algorithm for QRS detection [20, 25] is provided as a benchmark for algorithm comparison.

All the 10-s ECG episodes are challenging for QRS detection, as well as for HR estimation. In general, there are several signal types of the challenging ECG episodes. We summarize the signal types as follows.

2.1. Type A: Pathological Arrythmias

The abnormal heart beats, generated by the irregularity in the origin/conduction of the cardiac electrical activity, mainly include the following: left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contractions (PVC) (see Fig. 1). We did not indicate the ECG episodes from a special ECG channel. These episodes can be from any of the 12 ECG leads. Thus, the morphology of the ECG episodes varies. Traditional threshold algorithms (usually amplitude threshold) exhibit poor performance when deal with the small amplitude of QRS complexes caused by abnormal heart beats.

When bundle branch block occurs, one branch of His-bundle delays conducting the electrical impulse and ventricle is activated by the myocardial propagation of electrical activity from other ventricles. Thus, the affected ventricle is depolarized erratically and slowly through an alternative pathway. This delay is shown in ECG with a widening of QRS complex (duration >120 ms) and a change of its pattern, which varies depending on the affected branch, acted as RBBB or LBBB. Specific diagnostic criteria of RBBB and LBBB given by the ACC/ESC consensus document are summarized in Table I [26, 27].

PVCs are conducted by the specialized conduction system and therefore are broad. The QRS width is at least 120 ms, but often very broad around 160–200 ms. PVCs have many types and can be: monomorphic (QRS complexes with similar morphologies), multiformic (QRS complexes with different morphologies),

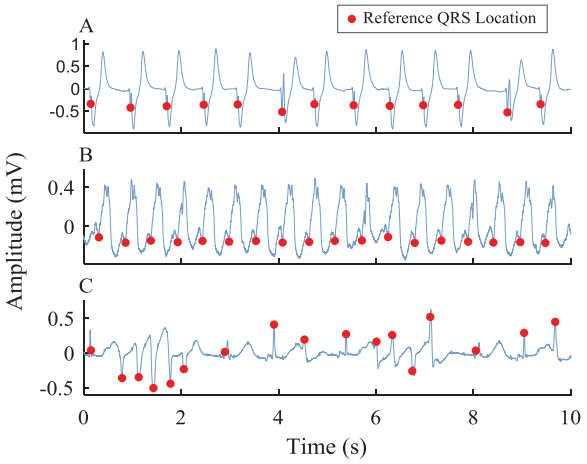

Fig. 1. From top to bottom: LBBB (data00872), RBBB (data00295), PVC (data00480). Red circles denote the reference QRS locations.

bigeminy (every sinus beat followed by a PVC), or trigemini (every second sinus beat followed by a PVC).

2.2. Type B: Sinus Tachycardia and Sinus Bradycardia

Sinus tachycardia and sinus bradycardia are sinus rhythms with a rate higher than 100 bpm or less than 60 bpm. In sinus tachycardia the sinus node fires between 100 and 180 impulses per minute. Maximal HR decreases with age from around 200 bpm to 140 bpm. In sinus bradycardia the sinus node fires at a slow (<60 bpm) rate. More severely, Sino-atrial exit block or sinus arrest may occur during sinus bradycardia and cause a long break. All these sinus tachycardia and sinus bradycardia put a challenge to the fixed threshold algorithms. Figure 2 shows two examples of sinus tachycardia and sinus bradycardia.

2.3. Type C: Poor Signal Quality Due to Artifact and Noise

Dynamic and wearable ECGs are easily contaminated by artifacts and noises. Worse yet, often the frequency content of noises overlaps with the frequency band of signal interest (thus limiting denoising approaches in the frequency domain) or has morphology similar to the QRS complex (thus limiting denoising approaches in the time domain) [28]. The typical artifacts and noises (Fig. 3) are from:

(1) Electrode contact noise: Loss of contact between the electrode and skin manifesting as sharp changes with saturation on the ECGs (usually due to an electrode being nearly or completely pulled off).

Table I. Diagnostic criteria of RBBB and LBBB.

RBBB	LBBB
QRS duration greater than 120 ms	QRS duration greater than 120 ms
rsR' "bunny ear" pattern in the anterior precordial leads (leads V1–V3)	Monomorphic R wave in leads I, V5 and V6 with no Q waves
Slurred S waves in leads I, aVL and frequently V5 and V6	ST and T wave opposite to the major deflection of the QRS complex

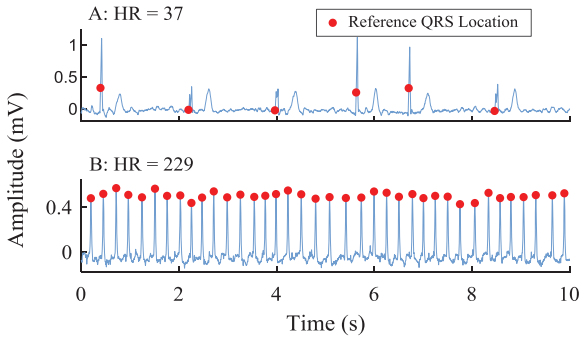

Fig. 2. Example of bradycardia (A: data00134), tachycardia (B: data00470). Red circles denote the reference QRS locations.

(2) Electrode movement artifacts: Electrode movement away from the contact area on the skin, leading to variations in the impedance between the electrode and skin, which will cause potential variations in the ECG and usually manifest themselves as rapid (but continuous) baseline jumps or complete saturation. (3) Device noise: Noises generated by the hardware of the device.

Unfortunately, ECG is often contaminated by noise in similar morphologies caused the interest signal nearly invisible by human eyes. To remove all noises completely is impossible, so it is important to quantify the nature of noises in a particular dataset and choose an appropriate algorithm.

2.4. Annotation

All raw ECG recordings (12 leads, 9364 normal or abnormal recordings) were beat-by-beat annotated first by the P&T QRS detector and then manually hand-corrected by visual inspection. The algorithm generally places beat annotations in the middle of the QRS complex (as determined from all 12 leads); the locations have not been manually corrected, however, and there may be occasional misaligned annotations as a result. Poor quality channels (as judged by the researcher performing the hand correction) of 12-lead recordings were picked and put into different types datasets as outlined above. Subsequently, manual review was performed by a single individual to correct any obvious mistake.

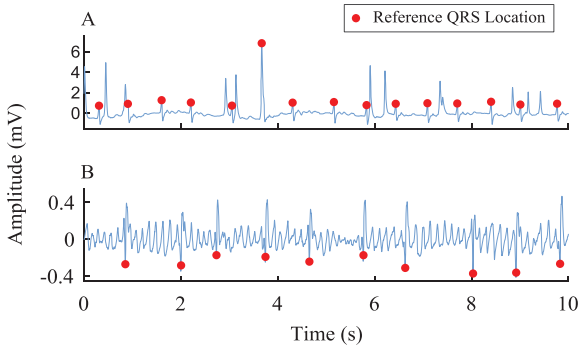

Fig. 3. Examples of poor signal quality ECG episodes due to artifacts (A: data00079) and noise (B: data00573). Red circles denote the reference QRS locations.

3. EVALUATION METHOD

The Challenge is comprised of two events related to scoring: QRS location and HR estimation. Only test set will be used for event scoring. QRS annotations in the training and test sets are labeled and approved by cardiologists and trained volunteers. These reference annotations have been processed to derive the reference RR interval time series (the intervals between successive QRS annotations). HR is further derived from the RR interval with a 4-s time window ranging from 5.5 s to 9.5 s in each of 10-s ECG segment. Pan & Tompkin algorithm for QRS detection is used as a benchmark method, and it outputs a score of 0.3345 for QRS detection task and 0.5299 for HR estimation task respectively.

3.1. Event 1: QRS Detection

In this event, the goal is to produce a set of QRS annotations that can matches the reference QRS annotations. For each reference QRS annotation, a matched QRS annotation should lie in 75 ms duration centered by the reference QRS annotation [29]. Noted that the reference QRS annotations appear in the first and last half seconds are omitted. As shows in Figure 4, detected QRS must be within 75 ms from the reference ones. For each 10-s ECG segment, the scoring rules are:

- complete matching scores one point;
- a false positive (FP) detection scores 0.7 points;
- a false negative (FN) detection scores 0.3 points, since from a clinical perspective, missed diagnosis is more serious than misdiagnosis, thus we penalize FN detection here;
- other situations score 0.

$$\mathrm{QRS}_{\mathrm{score}} = \begin{cases} 1 & \mathrm{FP} + \mathrm{FN} = 0 \\ 0.7 & \mathrm{FP} = 1 \text{ and } \mathrm{FN} = 0 \\ 0.3 & \mathrm{FP} = 0 \text{ and } \mathrm{FN} = 1 \\ 0 & \text{others} \end{cases}$$

The final score for Event 1 ($\mathrm{QRS}_{\mathrm{acc}}$) can be calculated as:

$$\mathrm{QRS}_{\mathrm{acc}} = \frac{\sum \mathrm{QRS}_{\mathrm{score}}}{\text{number of test recordings}}$$

3.2. Event 2: HR Estimation

In this event, the goal is to produce a real-time estimate for HR for a 4-s ECG episode, i.e., ECG signals from 5.5 s to 9.5 s. Figure 5 demonstrates the evaluation method for Event 2, i.e., how $\mathrm{HR}_{\mathrm{score}}$ for each 10-s ECG segment can be obtained.

The detailed scoring rules for HR estimation in each 10-s ECG segment are summarized as:

$$\mathrm{HR}_{\mathrm{score}} = \begin{cases} 1 & |\mathrm{HR}_{\mathrm{ref}} - \mathrm{HR}_{\mathrm{test}}| \le 0.02 \times \mathrm{HR}_{\mathrm{ref}} \\ 0.75 & 0.02 \times \mathrm{HR}_{\mathrm{ref}} < |\mathrm{HR}_{\mathrm{ref}} - \mathrm{HR}_{\mathrm{test}}| \le 0.05 \times \mathrm{HR}_{\mathrm{ref}} \\ 0.5 & 0.05 \times \mathrm{HR}_{\mathrm{ref}} < |\mathrm{HR}_{\mathrm{ref}} - \mathrm{HR}_{\mathrm{test}}| \le 0.1 \times \mathrm{HR}_{\mathrm{ref}} \\ 0.25 & 0.1 \times \mathrm{HR}_{\mathrm{ref}} < |\mathrm{HR}_{\mathrm{ref}} - \mathrm{HR}_{\mathrm{test}}| \le 0.2 \times \mathrm{HR}_{\mathrm{ref}} \\ 0 & 0.2 \times \mathrm{HR}_{\mathrm{ref}} < |\mathrm{HR}_{\mathrm{ref}} - \mathrm{HR}_{\mathrm{test}}| \end{cases}$$

The final score for Event 2 ($\mathrm{HR}_{\mathrm{acc}}$) can be calculated as:

$$\mathrm{HR}_{\mathrm{acc}} = \frac{\sum \mathrm{HR}_{\mathrm{score}}}{\text{number of test recordings}}$$

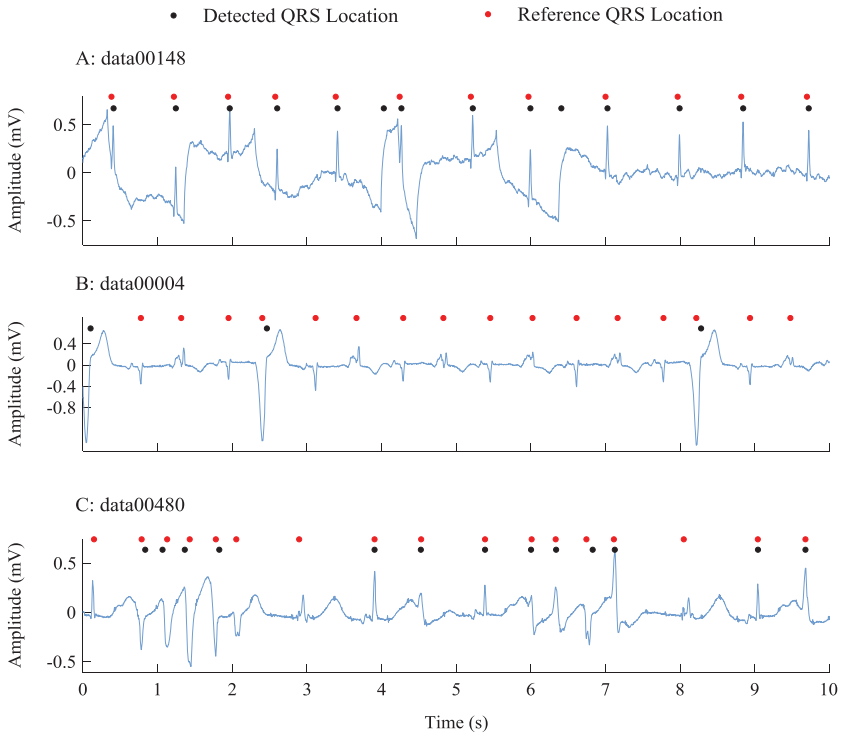

Fig. 4. Examples of the represented ECG waveforms. Red circles denote the reference QRS locations and black ones denote the detected results by the P&T algorithm.

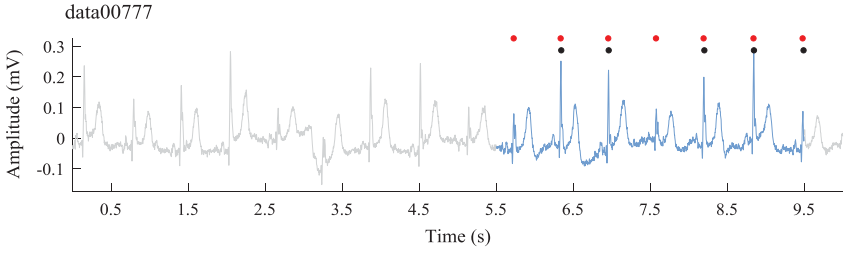

Fig. 5. Demonstration of the evaluation method for event 2. In this situation, reference HR can be calculated from the reference QRS annotations between 5.5 s and 9.5 s ECG episode ($HR_{ref} = 96$), and estimated HR can be calculated from the detected QRS annotations between the same 4-s ECG episode ($HR_{test} = 76$).

where HR_{test} and HR_{ref} represent HR calculated by competitor and reference, respectively. HR estimation is usually derived from the QRS detection but we encourage participant to develop robust HR estimation without QRS information.

4. DISCUSSION

In this paper, a brand-new database is presented aiming at promoting the development of robust QRS detection and HR estimation algorithms. Although several standard ECG databases (see Table II) [21, 30–32] are available for the evaluation of QRS detection algorithms and test on these well-annotated and validated databases provide reproducible and comparable results, the too high scoring performances are often obtained in these databases since the relatively good signal quality of ECG waveforms. But for all this, the existing QRS detection algorithms are not faced on the strict even rigorous testing. We emphasize on this point and address on it by developing a new ECG database with challenging QRS detection and HR estimation tasks, as well as propose a new evaluation rule for algorithm test in the developed challenging ECG database.

Currently, portable battery-operated systems such as mobile phones with wireless ECG sensors have the potential to be used in continuous and real-time cardiac function assessment that can be easily integrated into daily life. However, detection results for HR calculation on these dynamic ECGs are unsatisfactory. CPSC 2019 contains 2000 challenging 10-s ECG episodes with manually annotated QRS locations. This database includes signals from both pathological rhythm and artifacts, and is a real-world collected ECG database from the wearable device. We hope this strictly manual annotated database can benefit the study for dynamic ECG processing.

Table II. Summary of the major databases used for ECG signal analysis.

Database	# recordings	Data descriptions	QRS annotation	Other information
MIT-BIH arrhythmia[a]	• 48	• 30-min length • 2-channel • 360 Hz	• Beat-by-beat annotations for each beat in each recording (approx. 119 000 annotations) • 15 QRS beat types	• Rhythm label annotations
American heart association ventricular arrhythmia database[a]	• 80	• 35-min length for short version 3-h length for long version • 2-channel • 250 Hz	• Beat-by-beat annotations for final 30 min • 8 QRS beat types	• Classified according the level of ventricular ectopy
QT database[a]	• 105	• 15-min excerpts • 2-channel • 250 Hz	• Beat-by-beat annotations for each beat in each recording (total of 3622 beats)	• ST-T morphologies • segmentation of waveforms (for 30 to 100 beats per recording)
T-wave alternans database[a]	• 100	• 2-min ECG • 12-channel or 2 or 3-channel • 500 Hz	• Beat-by-beat annotations for each beat in each recording (total of 19003 beats)	• T-wave alternans information
Supraventricular arrhythmia database[a]	• 78	• 30-min ECG • 2-channel • 128 Hz	• Beat-by-beat annotations for each beat in each recording (total of 184744 beats)	–
Fantasia database[a]	• 40	• 120-min ECG • 3-channel • 250 Hz	• Beat-by-beat annotations for each beat in each recording (total of 278 996 beats)	• 1 channel for respiration • 20 single-lead for non-invasive blood pressure signal
Noise stress test database[a]	• 15	• 30-min ECG • 2-channel • 360 Hz	• Beat-by-beat annotations for each beat in each recording (total of 26, 370 beats under noise conditions)	• Noise was added two-minute segments alternating with two-minute clean segments in final 3 recordings
MIT ST change database[a]	• 28	• Varying lengths • 2-channel • 360 Hz	• Beat-by-beat annotations for each beat in each recording (total of 76 181 beats)	• Recorded during exercise stress tests
PTB[a]	• 268	• Varying lengths • 16-channel • 1000 Hz	• Beat-by-beat annotations for each beat in each recording • 9 QRS beat types	• 14-channel ECG • 1 channel for respiration • 1 channel for voltage
INCART[a]	• 75	• 30-min ECG • 12-channel • 275 Hz	• Beat-by-beat annotations for each beat in each recording (total 175 918 beat annotations) • 10 QRS beat types	–
UCI machine learning: Arrhythmia dataset	• 452	• 24-h ECG • 12-channel	• Diagnostic labeling • No QRS annotation • 16 QRS beat types	• 279 attributes (age, sex, height, waveforms description over 12 leads such as duration, amplitudes, areas)
Long-term-ST[a]	• 86	• Between 21 and 24 h • 2 or 3 ECG signals • 250 Hz	• Automatically-generated, manually-corrected QRS beat annotations	• Annotated ST episode • ST level measures • Signal quality annotations
European ST-T database[a]	• 90	• 2-h ECG • 2-channel • 250 Hz	• Beat-by-beat annotations by a slope-sensitive QRS detector and then checked by cardiologist	• Annotated ST change • T-wave morphology rhythm • Signal quality annotations
MGH/MF waveform database	• 250	• Varying lengths • 3-channel • 360 Hz	• Beat-by-beat annotations for each beat in each recording	• Include arterial pressure, pulmonary arterial pressure, central venous pressure, respiratory impedance, and airway CO_2 waveforms
1st CPSC	• 6,877	• Varying lengths • 12-channel • 500 Hz	• Diagnostic labeling • No QRS annotation • 9 ECG rhythm/morphology types	–

Note: [a]From PhysioBank datasets [21] available at https://physionet.org/.

Conflicts of Interest Statement

There is no conflict of interest to this work.

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