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Short communication

A novel single-arm-worn 24 h heart disease monitor empowered by machine intelligence

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ABSTRACT

A novel single-arm-worn ECG-based heart disease monitor is proposed in this paper. It is of a potential to provide continuous monitoring of different ECG metrics, and in this study, we focus on the duration of the QRS complex which is the central of an ECG heartbeat. Firstly, to avoid the low wearability induced by traditional chest-ECG or two-wrist ECG, we apply a highly wearable non-standard single-arm-ECG configuration. Afterwards, to estimate the QRS duration from noisy and weak non-standard single-arm-ECG, we propose a new three-stage machine learning framework. It firstly identifies heartbeat locations (R peaks) by a support vector machine classifier, then uses a dynamic time warping approach to locate QRS patterns that are similar to a template learned by a K-medoids clustering method, and finally learns to use the arm-ECG-based QRS duration estimates to predict a standard chest-ECG-based QRS duration trend. Experimental results demonstrate the effectiveness of this novel system, based on data collected from five subjects using our customized hardware prototype and the non-standard signal-arm-ECG configuration. To the best of our knowledge, this is the first study on the a single-arm-worn ECG-based daily heart disease monitor, using advanced signal sensing and machine learning techniques.

1. Introduction

Heart disease is a leading cause of death worldwide according to reports of World Health Organization [1], so how to effectively predict, diagnose and treat heart disease has become a big challenge for the whole society. As a critical vital sign, Electrocardiograph (ECG) has been attracting intense attentions in heart health management. In this study, we take special interest in ECG QRS duration (a QRS complex is the central part of an ECG heartbeat), which is associated with many heart diseases. For instance, a prolonged QRS duration may be related to sudden death risk in coronary disease [2], and a decreased one may result from reduction of right ventricular volume [3]. To deal with these unpredictable emergencies or chronic heart failure, ECG QRS duration monitoring should be both real-time and long-term, which is usually inconvenient and expensive in traditional medical infrastructures.

Wearable computers are boosting new healthcare solutions [4]. Many chest-worn ECG sensing systems have been reported for real-time and long-term QRS duration monitoring [5,6]. However, placing electrodes on the chest (usually with a chest strap) may induce inconvenience and uncomfortableness, especially when sweating. We are interested in whether we can use single-arm-ECG to estimate the QRS duration, since the ECG electrodes can be easily integrated into an arm band to provide a high wearability. Previously, we have studies the single-arm-ECG, but we focused on the blood pressure monitoring using it and also the single-arm photoplethysmogram [7]. There is no study about whether the single-arm-ECG can be used for continuous QRS duration estimation, which needs different machine learning algorithms to identify the QRS boundaries and also calibrate the estimates referring to standard chest-ECG-based readings.

In this paper, we demonstrate the feasibility of highly-wearable QRS duration tracking with the weak and noisy non-standard single-arm-ECG signal, empowered by machine learning techniques. To the best of our knowledge, it is the first work to explore single-arm-based ECG QRS duration monitoring. We firstly apply the support vector machine (SVM) for heartbeat identification. Afterwards, to robustly identify Q and S locations from the noisy ECG heartbeats due to this non-standard lead configuration, we propose a dynamic time warping (DTW)-based approach, which dynamically matches heartbeats with a high quality representative heartbeat learned by a K-medoid clustering method. Afterwards,

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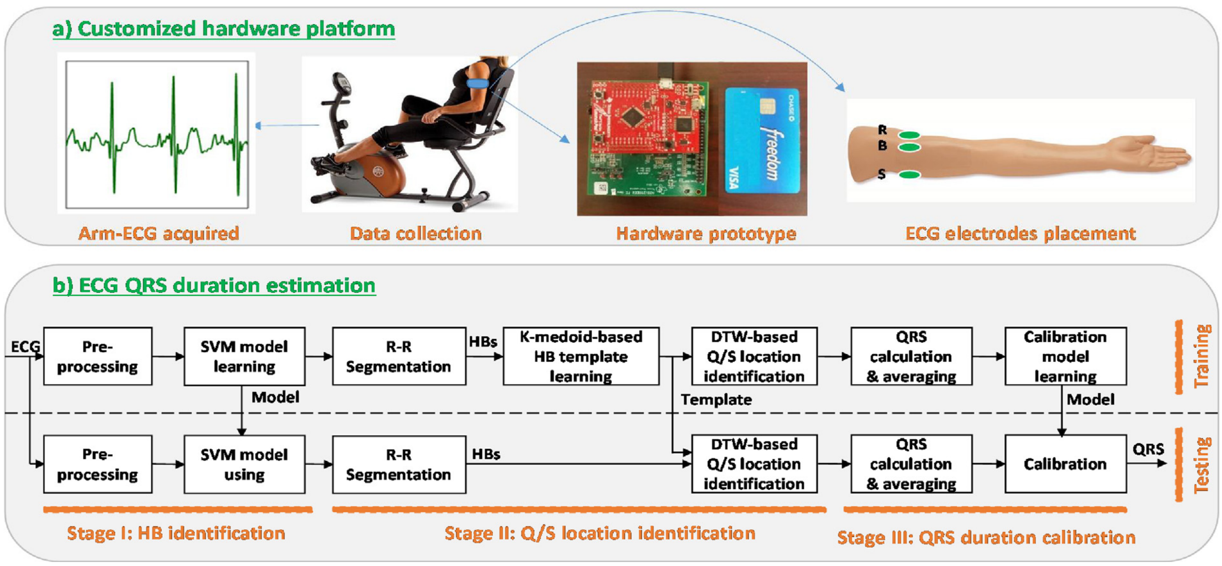

Fig. 1. System diagram of the proposed novel easy-wearing heart disease monitor (10 cm × 10 cm). R/B/S: reference/bias/signal electrodes; SVM: support vector machine; R-R: R peak to R peak; HB: heartbeat; DTW: dynamic time warping.

a QRS duration calibration model is learned based on the difference between the arm-ECG QRS duration and the chest-ECG QRS duration, and is then used to estimate the chest-ECG QRS duration from unseen arm-ECG data. This novel study is expected to advance easy-wearing ECG-based heart heath monitoring applications.

2. Materials and methods

2.1. System diagram

The proposed system is visualized in Fig. 1. The top part gives the customized hardware platform. The bottom part illustrates the ECG QRS duration estimation algorithm that includes a training and a testing phase. Details are given later following the signal processing flow.

2.2. Platform and dataset

The customized hardware platform includes two parts, i.e., a TI ADS1299EEG-FE board (blue one) that has a 24-bit analog-to-digital converter for low voltage bio-potential acquisition, and a TI TivaTM C series Launchpad (red one) for configuration and data transfer purposes. ECG electrodes was placed on the left upper-arm and the signal-to-reference electrodes distance was maximized to obtain more heart potential difference. Using this platform, a single-arm dataset including ECG was previously reported [7]. In this study, we evaluate the feasibility of single-arm-worn ECG-based QRS duration tracking solution.

Data collection for each of the five subjects included two 26 min sessions, for algorithms training and testing, respectively. Each session included 13 2 min trials. In trials 1, 12 and 13, the subject stayed still. In trails 2–11, the subject was asked to ride the bike in the first minute for heartrate perturbation purpose, and stay still in the second minute. The second minute data of each trail is used for algorithm evaluation. Fig. 2 gives an example, showing that the single-arm-ECG is very weak and its peak-to-peak voltage is only about 10% of that of chest-ECG.

2.3. SVM-based heartbeat identification

After pre-processing the raw ECG data using a six-order Butterworth band-pass filter (2–30 Hz) for baseline wander and

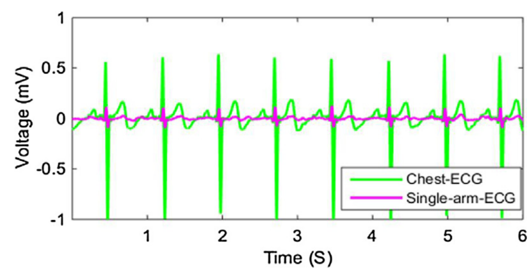

Fig. 2. An example of the acquired single-arm-ECG, showing that the peak-to-peak voltage of the single-arm-ECG is only around 10% of that of the chest-ECG (more details of the noisy characteristics will be visualized later).

powerline interference removal, an SVM classifier is firstly learned on the training data and then used onto the fresh testing data, for heartbeat identification purpose, as shown in stage I (Fig. 1). Features selected previously using a Sparse-SVM reported are extracted [8], which include R peak angle, S valley angle, R-to-S voltage drop, R peak symmetry, S valley symmetry, Skewness/Variance/Root mean square of the R peak region, and Angles of the slop of left/right R peak regions. Then from signal spikes that may include both real and faking heartbeats, we extract above features, and feed them into an SVM classifier. During training process, the SVM learns a hyperplane to separate the real heartbeats and the faking heartbeat. Afterwards, in the testing process, the learned hyperplane can be used to identify real heartbeats from fresh unseen data.

2.4. DTW-based QRS boundaries identification

After identifying R peaks and segmenting heartbeats, we now need to identify QRS boundaries, to estimate the QRS durations. Fig. 3 gives two examples of the identified QRS boundaries (onset of Q wave Q_L and offset of S wave S_R) for the single-arm-ECG and also chest-ECG (for comparison purpose), using a simple method that searches a nearest local maximum on the left and right side of the R peak, respectively. Comparing with the chest-ECG, it is hard to robustly identify all the QRS boundaries for the single-arm-ECG due to a much weaker signal strength (Fig. 2) and a much poorer signal morphology (Fig. 3).