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Development of ECG beat segmentation method by combining lowpass filter and irregular R–R interval checkup strategy

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ABSTRACT

We have developed a long-term cardiorespiratory sensor system that includes a wearable sensor probe with adaptive hardware filters and data processing algorithms (Choi & Jiang, 2006, 2008). However, the data processing algorithm proposed for the R–R interval (RRI) information extraction did not work well in the case of ECG signals with baseline shifts or muscle artifacts. Furthermore, many false ECG beats were extracted due to a weak decision-making scheme. Then, those false beats produced irregular RRI information and erroneous heart rate variability results. Modification of data processing algorithm was strongly needed. Therefore, this work presented an efficient ECG beat segmentation method using an irregular RRI checkup strategy into five sequential RRI patterns. This algorithm was comprised of signal processing stage and ECG beat detector stage. The signal processing included the wavelet denoising, the baseline shift elimination by 20 Hz lowpass filter and the envelope curve extraction by a single degree of freedom analytical model. The ECG beat detector included the candidate ECG beat detection and segmentation by one threshold and by irregular RRI checkup strategy, respectively. In particular, four abnormal RRI patterns were proposed to find out false ECG beats. The MIT-BIH arrhythmia database was selected as the dataset for testing the proposed algorithm. The proposed irregular RRI checkup strategy estimated 5463 beats to the suspected false beats and succeeded in segmenting 96.19% (5255 beats) of them. The performance results showed that our algorithm had very good results such as the detection error of 0.54%, sensitivity of 99.66% and positive predictivity of 99.80%. Furthermore, our algorithm showed very high accuracy as the mean time error between the beat annotations of the database and our obtained beat occurence times was 7.75 ms.

1. Introduction

The electrocardiogram (ECG) is the oldest and most commonly used cardiology method. Einthoven introduced methods of calibrating and correcting records obtained from the capillary electrometer, and predicted finally an ECG signal. The notation of ECG waveform suggested by Einthoven is in use until today, i.e., PQRST consisting mainly of P wave, QRS complex and T wave. The ECG generally needs to be recorded over a long-term because certain abnormalities might occur during sleep or with mental and emotional changes in cardiac function (Choi & Jiang, 2006, 2008). Therefore, ambulatory ECG recordings are used in clinical and theoretical researches to detect and characterize occurrences of abnormal cardiac electrical behavior during ordinary daily activities (Kadish et al., 2001).

In the ECG, QRS complex may be the most significant feature among all ECG features. The QRS complex detection provides important information for instantaneous heart rate computation because the accuracy of instantaneous cardiac cycle estimation relies on its performance (Clifford, Azuaje, & McSharry, 2006). However, it is difficult to implement the algorithm to identify the QRS complexes since QRS complexes are varying with the physiological variability and affected easily by the various noise sources such as motion artifact, 50/60 Hz power interference, baseline shift, T wave and more.

Therefore, in order to improve the accuracy of the QRS complex segmentation, many different approaches have been reported in literature, i.e., Hilbert transform (Benitez, Gaydecki, Zaidi, & Fitzpatrick, 2001), moving average filter or wavelet denoising (Chen, Chen, & Chan, 2006; Christov, 2004), phase portraits

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(Cvikl, Jager, & Zemva, 2007; Lee, Kim, Lee, Lee, & Lee, 2002), genetic algorithm (Poli, Cagnoni, & Valli, 1995), hardware filter banks (Afonso, Tompkins, Nguyen, & Luo, 1999), R–R interval (RRI) (Christov, 2004; Pan & Tompkins, 1985) and the morphological processing (Hamilton & Tompkins, 1986; Pan & Tompkins, 1985; Paoletti & Marchesi, 2006). Most approaches related to the QRS complex detection can mainly be divided into two stages as signal processing and QRS detector based on one or more threshold values (THVs). The major signal processing and detector methods, together with our method proposed in this study, are summarized in Table 1. For the signal processing stage, Benitez et al. (2001) presented the use of the first differential of the ECG signals and its Hilbert transform (Bolton & Westphal, 1981). Christov (2004) used the summation and differentiation processes of the noise-canceled signals by moving average filter for one or more ECG leads. Sequential filtering method such as wavelet denoising, moving average filter based highpass filter and lowpass filter was proposed by Chen et al. (2006). Lee et al. (2002) and Cvikl et al. (2007) tried to process the ECG signals by using phase portraits based on delay-coordinate mapping method. Poli et al. (1995) proposed the polynomial filters. Afonso et al. (1999) designed a signal processing algorithm based on filter bank strategy. Finally, the morphological approaches such as slope and amplitude by derivative and squaring or integration processing were used by Pan and Tompkins (1985), Hamilton and Tompkins (1986) and Paoletti and Marchesi (2006). For the detector stage, on the other hand, approximation (Benitez et al., 2001), one adaptive THV (Benitez et al., 2001; Chen et al., 2006), multi-adaptive THVs (Afonso et al., 1999; Christov, 2004; Cvikl et al., 2007; Hamilton & Tompkins, 1986; Lee et al., 2002; Pan & Tompkins, 1985; Paoletti & Marchesi, 2006; Poli et al., 1995) and rule-based decision system (Cvikl et al., 2007; Hamilton & Tompkins, 1986; Lee et al., 2002) were frequently used to search the QRS complexes. However, most approaches are complex and are involved with high computational costs because of using complicated checkup strategy and multiple THVs in the decision-making stage. Some approaches might be inapplicable in real time.

In this paper, we introduce a simple ECG beat segmentation algorithm. The method consists of two stages such as signal processing and ECG beat detector. In the signal processing stage, the wavelet denoising and lowpass filter approaches are used to cancel the unwanted components corrupted in the ECG. Then the envelope curve is calculated. In the ECG beat detector stage, the candidate ECG beats are extracted first by applying one adaptive THV to the extracted envelope curve. However, these candidate beats may include many spurious beats and the resulting RRI information may produce irregular time duration as short or long. Thus, to filter out those suspected false beats, an irregular RRI checkup strategy via the five most-recent sequential RRI patterns is introduced. The abnormal patterns with one or more irregular RRIs showed four possible combinations. Furthermore, the MIT-BIH arrhythmia database is used to test and validate the efficiency of our algorithm. The performance results showed that our algorithm is successful in detecting correctly 99.46% of the ECG beats. The sensitivity and positive predictive rate are 99.66% and 99.80%, respectively. In the segmentation step, 5463 suspected false beats are detected and 5255 beats among them were segmented and recalcualted. Our performance results and other researches' results were also compared for validating the efficiency of our simple ECG beat segmentation algorithm.

2. MIT-BIH arrhythmia database

In this study, the MIT-BIH arrhythmia database (MITDB) (MIT-BIH Arrhythmia Database, 2008) was used as the dataset of ambulatory ECG monitoring. The MITDB contains 48 records obtained from 47 subjects that consist of 25 males aged 32–89 yr and 22 females aged 23–89 yr. Each record is slightly over 30 min long and consists of the upper and lower leads. Since normal QRS complexes might be usually prominent in the upper lead, the upper lead was used as a default. Each ECG recordings were digitized at 11 bit-depth and 360 Hz. The MITDB includes the annotation information for each record, i.e., rhythm labels, signal quality labels, and comments and the time index of occurrence of each QRS complex. The annotated time indices for each record were used for validation of our algorithm.

Fig. 1 plots four example waveforms and the ECG beats of the records 101, 222, 104 and 203, selected from the MITDB. Fig. 1a and b shows the original ECG waveforms for the records 101 (a female aged 75 yr) and 222 (a female aged 84 yr). Fig. 1a is a case with severe abrupt change in potential and Fig. 1b is an ECG signal with the influence of the respiratory related rhythms and muscle artifacts. Marks '●' indicate the normal beats. Fig. 1c and d shows the original ECG waveforms for the records 104 (a female aged 66 yr) and 203 (a male aged 43 yr). Fig. 1c is an ECG signal with the influence of muscle artifacts. The fusion of paced and normal beats is marked by '◎' and the unclassifiable beats are marked by '⧫'. Fig. 1d is a case with QRS morphology changes due to axis shifts, and with the influence of muscle artifacts and baseline shifts. Marks '●' and '◇' indicate the normal beats and premature ventricular contractions (PVCs), respectively. From Fig. 1, it seems difficult to discriminate clearly the ECG beats from the cases with serious distortion of the ECG caused by considerable noises (Fig. 1c and d), as compared with less noisy signals (Fig. 1a and b). Furthermore, it is obvious that those unwanted components lead to low performance results in the ECG segmentation. Thus, some adaptive data processing and robust detection algorithms should be considered and applied to the case of the ECG contaminated with baseline shifts, muscle artifacts and noises. However, most approaches are somewhat complex and need high computational costs due to multiple THVs and complicated detection rules. And then, in order

Table 1
Summary of various researches for ECG beat segmentation.

Author	Major signal processing method	Major detector
Benitez et al. (2001)	Hilbert transform and 1st differential	One adaptive THV and 1st approximation
Christov (2004)	Moving average filter	Combined three adaptive THVs or RRI
Chen et al. (2006)	Wavelet denoising and moving average filter	One adaptive THV
Lee et al. (2002)	Phase portrait and lowpass filter	Two THVs, refractory blanking and search back
Cvikl et al. (2007)	Phase portrait and bandpass filter	Two THVs, refractory blanking and search back
Poli et al. (1995)	Polynomial filter	Three adaptive THVs
Afonso et al. (1999)	Filter bank	Three THVs and timing information
Pan and Tompkins (1985)	Morphological processing	Four adaptive THVs and the average RRI information
Hamilton and Tompkins (1986)	Morphological processing	Three adaptive THVs, refractory blanking and search back
Paoletti and Marchesi (2006)	Morphological processing	Four adaptive THVs and cluster analysis
Our algorithm	Wavelet denoising and lowpass filter	One adaptive THV and RRI patterns