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A multiresolution time-dependent entropy method for QRS complex detection

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ABSTRACT

Electrocardiography is considered as a useful diagnostic tool for evaluating the condition of heart's health. QRS complex, which is produced by depolarization of the heart ventricles, is the main graphical deflection seen on a typical electrocardiogram tracing. Detection of the QRS complexes is the first step toward analyzing the electrocardiogram signal. In this regard, many different algorithms have been proposed so far. In the present work an algorithm based on entropy measure is proposed which uses the calculation of the time dependent entropy for QRS complex detection. The algorithm is implemented in a way that entropy of the electrocardiogram can be calculated in different temporal resolution to improve the accurate detection rate of different QRS morphologies. The MIT-BIH arrhythmia and CSE databases are selected to test the performance of the proposed algorithm. The precision and sensitivity of the proposed method for MIT-BIH database are 99.85% and 99.75%, respectively. Also the detection rate of 99.82% is achieved for CSE database. Additionally, the proposed algorithm is fast enough to be applied in real-time.

1. Introduction

Electrocardiogram (ECG) is the most common diagnostic tool for evaluating the heart's health condition and contains valuable information about the performance of the heart. A typical ECG tracing of the cardiac cycle consists of recurrent wave sequence of *P*, QRS and *T*-wave. The QRS complex, which is produced as a result of the depolarization of the heart ventricles, is the main graphical deflection seen on a typical ECG tracing. Regularly, the detection of QRS complex is the first and easiest task for the majority of heart checkups. The typical checkups consist of ECG beat segmentation [1], R–R interval estimation for heart rate variability analysis [2] and ECG classification [3].

There have been several algorithms proposed for QRS complex detection. Pan and Tompkins suggested an algorithm (PT algorithm) [4], which consists of passing of ECG signal through a band-pass filter, differentiator and squaring blocks, for QRS complex detection. A Hilbert transform-based method, as an improved first-derivative based QRS detection method, was proposed by Benitez et al. [5] in which a variable threshold was determined without user intervention. Hilbert transform is an odd filter, therefore the zero-crossing of the differentiated ECG, which correspond to the R peaks, can be used for QRS complex detection [5]. A fractional digital differentiation-based algorithm (FDD) for R peak detection was proposed by Ferdi et al. [6]. In this method an FIR band-pass filter with coefficients that are only dependent on fractional order, reduces unrelated components in the ECG and produces peaks corresponding to the QRS complexes. Algorithms based on first order differentiated ECG are computationally efficient and have been exploited extensively in real-time QRS complex detection [7]. Arzeno et al. [8] compared the traditional first-derivative based algorithms for QRS detection and modified some of them with improved detection criteria. For example, in Hamilton–Tompkins algorithm [7] an automatic threshold adjustment has been performed to overcome the difficulty of manual threshold selection [8] (for comparison purposes this algorithm is called Modified HT algorithm). In another work, a method based on empirical mode decomposition (EMD) was proposed for QRS complex detection [9]. EMD algorithm is established on the assumption that time series are composed of some oscillatory modes, which are called intrinsic mode functions (IMF). The essential information for each frequency range would be contained in one IMF therefore the band-limited event such as QRS complex would be represented by only some successive IMFs. This fact can be used for the detection of QRS complexes. Wavelet transform has gained special attention in the QRS complex detection [10–13]. The wavelet transform provides multiresolution representation of the ECG signal where QRS complex with different energy (frequency) content can be distinguished from other ECG waves. However, the main drawback of this method is its sensitivity to the selection of wavelet

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basis function that affects the energy distribution among wavelet coefficients and hence the event detection efficiency. Also, there are methods based on artificial neural networks (ANNs) that have been used for QRS complex detection [14,15], which their training steps considerably need a-priori information about ECG signal. A non-linear energy transformation followed by a decision making rule was proposed by Gritzali [16] for QRS detection. In another work, time recursive prediction technique was used in single-lead and multi-lead ECG signals for QRS complex detection [17]. There are references that have used multi-channel ECG recordings for QRS complex detection. Among which *K*-means clustering algorithm [18] and *K*-nearest neighbors (KNN) [19] can be noted.

As the QRS complexes in ECG tracing change the entropy of the time series, methods that measure information content can be used for QRS complex detection. Entropy represents the average amount of information contained in random variables. By providing that definition, entropy criterion to enhance the QRS complexes in 12-lead ECG signal has been applied [20,21]. In another work, S-Transform has been used to access the frequency content of the QRS complexes and the Shannon entropy has been used to highlight QRS complexes [22]. Also, an algorithm based on Shannon energy envelope has been introduced to find out the R-peaks in the ECG signal [23].

In this paper an intuitive entropy-based method is proposed for QRS complex detection, which relies on the fact that QRS complexes can increase entropy significantly. Proposed entropy-based algorithm is able to describe the original ECG signal with different temporal resolution and hence highlights QRS complexes with different morphologies. Different QRS morphologies appear in the ECG recording specially when there are some abnormalities in the heart condition and these abnormal heart beat morphologies reduce the sensitivity and accuracy of common available algorithms [8]. The proposed method in this paper, seek to overcome such challenges. The time complexity of the proposed algorithm allows the real time application of the algorithm. The results of implementation of the proposed method confirm that its efficiency is comparable with the state-of-the-art methods in QRS detection and in some aspects such as computational complexity and real-time feasibility, its performance is better comparing to the traditional methods.

2. Material and methods

2.1. Preprocessing step

There are various types of noise and artifacts that affect the ECG signal. Baseline wander and EMG induced artifact are the most common types of these artifacts. Baseline wander is a low frequency component usually caused by respiration, body movement or poor electrode-skin contact and its frequency content is usually below 1 Hz. The frequencies of EMG artifact not only are considerably overlapped with QRS complex, but also their spectrum extends to higher frequencies. In order to reduce the effect of baseline wander and artifacts with higher frequencies, a multi-resolution wavelet based noise reduction scheme is used. In this regard, undecimated wavelet transform (UWT) is applied and the signal is decomposed in 9 levels. In order to reduce the effect of baseline wander, the last approximation level and to reduce high frequency artifacts the first detail level are selected respectively and thresholded based on (1).

$$\sigma = \frac{\text{Median}\left|x - \text{median}\,(x)\right|}{0.6745}$$
$$\text{thresh} = \sigma\sqrt{2\ln(l)} \tag{1}$$

where x represents the vector of wavelet coefficients in each level, 0.6745 is the 75th percentile of the standard normal distribution and l is the length of x. Soft thresholding based on estimated threshold (thresh) is applied to the detail coefficients at the first level and the approximation coefficients at the last level. It should be noted that the threshold estimation based on (1) is robust against outliers. In order to remove Baseline wander, nine decomposition levels are chosen. For sampling frequency of $fs < 500$ Hz, the frequency content of the approximation coefficients in 9th level is smaller than 1 Hz, while the frequency content of different types of QRS complexes is 2.5–10 Hz and consequently such selection guarantees the preservation of the QRS complexes and the elimination of the Baseline wander. Based on the thresholded wavelet coefficients, denoised ECG signal is reconstructed for further analysis.

2.2. Time dependent entropy (TDE)

Entropy represents the amount of uncertainty in a system, where higher entropy means more uncertainty. The depolarization of the ventricles of the human heart produces QRS complex as a sudden change in the ECG tracing that affects the entropy of the signal. In this regard, entropy is a powerful tool for identifying abrupt events like QRS complexes [24]. Conventional entropy estimation methods consider the overall uncertainty of the time series, therefore such methods cannot be used in event localization. In order to overcome this problem, TDE was introduced [25] where a sliding L-sample window is applied to the N-sample signal $\left\{s(\alpha) : \alpha = 1, \ldots, N\right\}$ and the entropy in each windowed signal segment is calculated. This makes it possible to find the time occurrence of an event. The L-sample windowed signal with T-sliding lag can be defined as the following equation:

$$W(m, L, T) = \left\{s(\alpha)\cdot w, \alpha = 1 + mT, \ldots, L + mT\right\} \tag{2}$$

where w is L-sample window, m is the window index and T is the sliding lag. T is usually chosen to be smaller than L in order to prevent missing abrupt events. Entropy measures the divergence from a probability density function (*pdf*) to a uniform distribution. When an abrupt event occurs, the amplitude distribution of the signal or its *pdf* will change and deviates from uniform shape and consequently exhibits a sharper profile. The simplest way to estimate *pdf* is histogram, where the range of signal is equally divided into some bins and the probability of the ith bin is defined as the ratio of the number of samples falling into that bin to the signal sample size.

There are different types of entropy measures. A more generalized form of entropy is Tsallis entropy (TE), which is expressed by (3) and can be quite useful in calculating entropy in the presence of transients [26].

$$\text{TE} = \frac{\left(1 - \sum_{i=1}^{v} P_i^q\right)}{(q-1)} \tag{3}$$

where q is the entropic index, V is the number of voltage bins in the selected segment of ECG and P_i is the probability of the ith bin in the histogram [27]. Based on (3), TE of windowed signal segment is calculated. The parameter q in (3) emphasizes the presence of abrupt changes like QRS events. By calculating TE in successive sliding windows in data stream the output of TDE is obtained which emphasizes QRS complexes by sharp valleys. With some simple mathematical operations, sharp peaks appear in TDE output. In order to weight events located in the window center, the Tukey window is chosen and multiplied by each windowed signal segment. The optimal parameters of TDE are discussed in Section 2.4.

For post-processing, exponential weighting scheme is used to produce smoothed version of TDE according to (4):

$$X_s(i) = sX_t(i-1) + s(1-s)X_t(i-2) + s(1-s)^2X_t(i-3) + \ldots \tag{4}$$