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Original

Feature extraction of electrocardiogram signals by applying adaptive threshold and principal component analysis

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Abstract

This paper presents a novel approach for QRS complex detection and extraction of electrocardiogram signals for different types of arrhythmias. Firstly, the ECG signal is filtered by a band pass filter, and then it is differentiated. After that, the Hilbert transform and the adaptive threshold technique are applied for QRS detection. Finally, the Principal Component Analysis is implemented to extract features from the ECG signal. Nineteen different records from the MIT-BIH arrhythmia database have been used to test the proposed method. A 96.28% of sensitivity and a 99.71% of positive predictivity are reported in this testing for QRS complexity detection, being a positive result in comparison with recent researches.

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Keywords: Adaptive threshold; Hilbert transform; Principal Component Analysis; Electrocardiogram signals

1. Introduction

Cardiovascular diseases are the main cause of death worldwide according to the World Health Organization (Alwan, 2011; Palanivel & Sukanesh, 2013). In 2008, around 17.3 million people have died from cardiovascular diseases, which represent 30% of all worldwide deaths (Alwan, 2011). Thereby, cardiac health research has acquired significative importance for medical researchers, mainly for those focused on technological, preventive and medical advances. Accordingly, traditional technologies for cardiovascular-diagnosis used at home, clinics and hospitals have been of main interest for researchers in order to improve them.

Electrocardiogram (ECG) analysis is the most common clinical cardiac examination, which is a useful detection tool for several cardiac abnormalities, mainly because it is inexpensive, simple and risk-free (Dilaveris et al., 1998; Elgendi et al., 2014). Hence, ECG analysis has been widely investigated during the last two decades. Mostly, because an ECG signal records a vital sign for heart functional investigation because it represents the electrophysiological events that coincide with the sequence of depolarization and repolarization of the atria and ventricles (Elgendi et al., 2014).

The three main events presented in the signal of each heartbeat are: the P wave, the QRS complex, and the T wave (Hasan & Mamun, 2012). Each event contains its own peak, making this important to analyze their morphology, amplitude, and duration for cardiac arrhythmias detection (Bashour et al., 2004; Tran et al., 2004; Tsipouras et al., 2002). Also, their analysis can be critical for detecting breathing disorders such as obstructive sleep apnea syndrome (Trinder et al., 2001; Zapanta et al., 2004) and for studying the autonomic regulation of the cardiovascular system during hypertension and sleep (Trinder et al., 2001). Other functional or structural cardiac disorders can be monitored too.

Computer-based ECG analysis requires an accurate detection of QRS complex, in particular, an accurate detection of the R wave. Nevertheless, this is a non-easy task since a real ECG signal usually faces muscular noise, motion artifacts, and baseline drifts changes (Benitez et al., 2001). Other components of an ECG, such as P and T waves, are also found to be high in some cases, and these waves must be differentiated from the QRS waves. This increases the complexity of QRS detection (Benitez et al., 2001; Köhler et al., 2003). False R-wave detection or the failure to detect R-waves may lead to undesired results in computer-based ECG analysis (Köhler et al., 2003). In addition, the number of false

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detections significantly increases in the presence of ECG signals from patients with pathologies or by using poor signal-to-noise ratios (SNR) (Burte & Ghongade, 2012; Köhler et al., 2003).

Several QRS detection researches have been developed during decades; these researches have been mainly attained to three categories: time domain detection techniques, transform domain detection techniques, and other methods that include morphologic filtering techniques and template matching (Burte & Ghongade, 2012). These techniques have been utilized into different applications like heart rate variability analysis, arrhythmia classification, heart rate calculation, feature extraction, ECG compression, R-R interval analysis, and P, S, and T wave detection (Burte & Ghongade, 2012).

QRS well-known algorithms are mainly focused on two important stages: QRS enhancement and QRS detection. The stage of QRS enhancement is applied to enlarge the QRS complex with respect to the other QRS features, such as P, T, and noise. In some researches, this stage is described as pre-processing or feature extraction. One of these techniques is the amplitude threshold which has been used by Morizet-Mahoudeaux et al. (1981). With this technique, the signal noise is not properly removed and it is usually followed by the first derivative of the ECG signal (Morizet-Mahoudeaux et al., 1981). Other technique is the first derivative of the ECG signal followed by threshold (Okada, 1979), this technique helps to reduce baseline drifts and motion artifacts (Zhang & Lian, 2007); however it does not remove high frequency noise. Some research work have applied first derivative combined with second derivative of an ECG signal, followed by threshold (Ahlstrom & Tompkins, 1983); although the signal noise is not removed properly. Digital filters have been applied by other authors for QRS enhancement. The applied digital filter can increase the SNR ratio; it depends on the order of the filter and its nature. In Pan and Tompkins (1985), authors applied a bandpass filter to an ECG signal followed by its first derivative, and threshold. In Yongli and Huilong (2005), authors applied mathematical morphology filtering to ECG signal for QRS enhancement followed by threshold. With the mathematical morphology algorithms the signal noise is partially addressed. According to the literature, authors have also been approaching the QRS enhancement by applying Empirical Mode Decomposition (EMD) filtering (Tang et al., 2008). In Tang et al. (2008), the EMD is applied to ECG signal followed by threshold. In this sense, the first several Intrinsic Mode Functions can preserve the QRS content; they are able to filter out the noise, and improve the SNR. Other research work have applied the Hilbert transform for QRS enhancement (Arzeno et al., 2008), also, the first derivative can be used before applying the Hilbert transform, and then be followed by threshold. However, the Hilbert transform does not improve the SNR; hence it is common for investigators to filter the signal before applying the Hilbert transform. Other technique applied for QRS enhancement is the filter banks, which significantly improve the SNR for Gaussian noise and for muscle noise in comparison with the median or mean averaging methods (Afonso et al., 1995). In Afonso et al. (1999), authors applied filter banks to ECG signal followed by threshold. Furthermore, the wavelet transform technique has also been used by other related work. I.e., in Dinh et al. (2001), authors applied wavelet transform to ECG signal followed by threshold; with wavelet transform, the SNR can be improved by selecting the coefficients with the largest amplitude (Alesanco et al., 2003).

Several techniques have been applied in the literature for QRS detection. Matched filters have been applied to ECG signal by Kaplan (1990). Another technique is the syntactic method, which has been applied by Trahanias and Skordalakis (1990) to detect QRS complex in ECG signal; however, the syntactic method is sensitive to noise (Trahanias & Skordalakis, 1990). In Liang-Yu et al. (2004), authors have applied wavelet transform to ECG signal followed by neural networks. It is important to note that neural networks are highly sensitive to noise (Clifford et al., 2006). Other technique is the Hidden Markov Model which has been used by Coast and Cano (1989), where authors applied a bandpass filter to the ECG signal followed by the Hidden Markov Model. However, Hidden Markov Model is sensitive to heart rate variation, baseline wander, and noise (Cheng & Chan, 1998). Singularity method is also applied by researchers for QRS detection (Xing & Huang, 2008). Xing and Huang (2008) applied the EMD filtering to an ECG signal; after that, authors applied the singularity and threshold methods. However, the singularity method is sensitive to noise (Ayat et al., 2009). In addition, zero-crossing technique has been applied in the literature for QRS complex detection. Köhler et al. (2003) firstly applied the bandpass filter to an ECG followed by a zero-crossing; however, this method is also sensitive to noise.

According to related work, methods based on Hilbert transform have the ability to discriminate the dominant peaks from other peaks. These methods have been capable to improve the results for R-wave detection. However, they tend to fail in diseases that cause low-amplitude waves, and in ischemic cases (Köhler et al., 2003). Normally, a threshold is needed for the detection of the R-wave in an electrocardiogram signal; a fixed threshold for detecting R-waves can be efficient and simple for ECG signals with normal beat morphology (Elgendi et al., 2014). However, several researchers have reported that ECG signal waveforms may vary drastically from each other, due to movement of patients, or severe baseline drifting. Accordingly to this, there is a high probability that QRS complexes may be missed. Otherwise, adaptive thresholding has been proven to reduce the probability of missing QRS complex detection (Elgendi et al., 2014; Köhler et al., 2003; Madeiro et al., 2007; Rabbani et al., 2011).

Usually, adaptive thresholding makes empirical use of many thresholds. In Li et al. (1995), authors presented an algorithm based on wavelet transform for detecting QRS complex, as well as *P* and *T* waves; a constant threshold has been used, which was determined empirically. Kadambe et al. (1999) used a constant threshold for QRS detection; the threshold has also been empirically determined. Their algorithm is based on wavelet transform too. In Burte and Ghongade (2012), and Xu and Liu (2005), authors have shown that adaptive thresholding provides interesting results for R wave peak detection. In their case, the thresholds have been detected automatically.

Moreover, according to specialized literature, Principal Component Analysis (PCA) has been used for extracting mo-

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