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DSP-based arrhythmia classification using wavelet transform and probabilistic neural network

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ABSTRACT

A large part of the biomedical research spectrum is dedicated to develop electrocardiogram (ECG) signal processing techniques to contribute to early diagnosis. However, it is common to find that ECG analysis methods reported are confined to off-line PC host operation. The authors present an arrhythmia classification method implemented on a Digital Signal Processing (DSP) platform intended for on-line, real-time ambulatory operation to classify eight heartbeat conditions: normal sinus rhythm (N), auricular fibrillation (AF), premature atrial contraction (PAC), left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contraction (PVC), sinoauricular heart block (SHB) and supraventricular tachycardia (SVT). The algorithm uses a wavelet transform process based on quadratic wavelets for identifying individual ECG waves and obtain a fiducial marker array. Classification is conducted by means of a Probabilistic Neural Network. The algorithm is tested with 17 ECG records obtained from the PhysioNet repository. The proposed classification procedure was tested initially on MATLAB and the results where compared with the equivalent analogue data fed to a DSP-based ECG data acquisition prototype through an arbitrary waveform generator. The results derived from confusion matrix tests yielded on-line classification accuracy of 92.69% (AF), 97.15% (N), 76.82% (PAC), 91.06% (LBBB), 87.5% (RBBB), 71.04% (PVC), 91.94% (SHB) and 95.45% (SVT), overall classification rate of 92.746% and 100% agreement between the MATLAB and on-line DSP implementations. The results suggest that the method and prototype presented may be suitable for being implemented on wearable sensing applications auxiliary for on-line, real-time diagnosis.

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1. Introduction

Cardiac arrhythmia occurs intermittently at early stages of heart disease which difficult early diagnosis. Undiagnosed cardiac arrhythmias often evolve undetected [1], reducing the effectiveness of treatment in advanced stages. In addition, tachyarrhythmic events are associated with sudden dead [2], occurring less than an hour after symptoms onset [3]. Thus, a large part of the biomedical research spectrum is directed towards developing electrocardiogram (ECG) diagnostic equipment and signal processing techniques [4] to contribute to early diagnosis so as to improve the effectiveness of heart disease treatment beginning at the early stages. On the other hand, current trends in ambulatory diagnostic equipment involve the use of remote implantable monitoring [5] and wearable sensing technologies [6] that may facilitate obtaining on-line real-time data for immediate, remote diagnosis. The advances in electronics technology during the last decade have contributed to the development of commercial, powerful mixed-signal data acquisition and processing devices, suitable for wearable sensor applications. Therefore methods for real-time cardiac arrhythmia detection for ambulatory data acquisition devices are continuously reported that may result in enhanced on-line detection of intermittent events that may otherwise be undetected. However, many ECG analysis results reported are confined to traditional, off-line, PC-based operation. Here, the authors address the importance of arrhythmia classification procedures intended for on-line operation and compare results obtained off-line with those processed through the DSP hardware developed for this application

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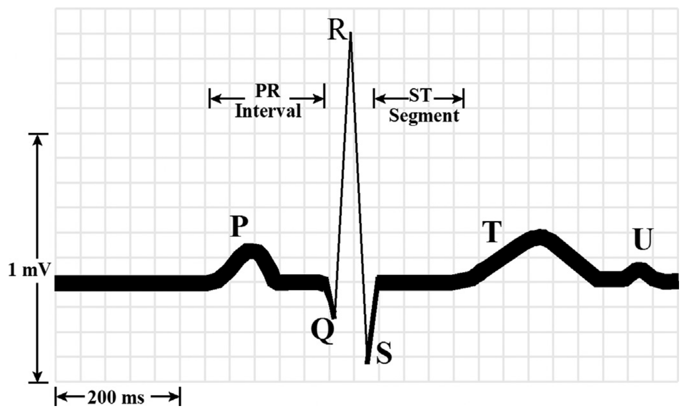

Fig. 1. Normal ECG pattern.

1.1. Arrhythmia classification procedures

The term arrhythmia is associated with changes of frequency, rhythm or morphology of the ECG signal in comparison with normal ECG values (Fig. 1).

In general, and in a very simplified manner, arrhythmia classification [7] from ECG graphical records involves 5 main steps:

(A) Calculate cardiac frequency. The heartbeat rate (HR) is considered normal between 60 beats per minute (bpm) and 100 bpm [8,9]. Based solely on HR, arrhythmias can be classified as bradyarrhytmias (HR < 60 bpm) and tachyarrhythmias (HR > 100 bpm). Cardiac frequency calculation is probably the easiest process that can be implemented on-line, and thus has become an integral part of ECG ASIC (Application Specific Integrated Circuits) hardware (i.e. Texas Instruments ADS129X series).
(B) Measure the RR interval. The R wave-to-R wave interval (RR) is an indicator of ventricular rate and should be regular with less than 0.12 s difference between heart beats.
(C) Examine the P wave. If the P wave precedes the QRS complex the impulse is generated in the SA node. The presence of abnormal locations of the P waves may indicate an ectopic pacemaker.
(D) Measure the PR Interval. The normal interval is considered between 0.1 and 0.2 s. A larger difference indicates a defect of the conduction system.
(E) Measure the QRS complex duration and morphology. If the width between the beginning of the Q wave and the end of the S wave is larger than 0.12 s, there may be an intraventricular conduction defect.

The steps outlined here do not intend to diminish in any way the complex nature of the ECG signal, but merely to serve as a starting point for highlighting some of the ECG prominent features that need to be analyzed that can lead to automated arrhythmia classification. In addition, the expertise of the specialist for analysing the graphical records, is a key factor in identifying heartbeat conditions related to specific cardiopathies.

Thus, achieving accurate automated arrhythmia diagnosis is a challenging goal that has to account for multiple heartbeat characteristics. For instance, supraventricular heart rhythm disorders include different types of arrhythmias, each one presenting different ECG signal signatures that defy the accuracy of detection and classification procedures. As an example, atrial fibrillation (AF) is considered the most common arrhythmia characterized by the absence of prominent P-waves often appearing as fibrillatory waves on the ECG record, and varying RR intervals. The prevalence of AF is of great interest for developing automated classification methods so as to aid diagnosis. However, the difficulties to correlate the absence of P-waves and irregular RR intervals or existing P waves in chaotic heart rhythms can lead to misdiagnosed atrial fibrillation [10]. The inherent difficulty of identifying the ECG waves corresponding to AF may also lead to automated classifications errors [11]. Supraventricular tachycardia is another example of an abnormal heart rhythm where there is an increase in heartbeat rate and the P-wave overlapping the narrow QRS complex [12]. Thus, in automated ECG analysis, there are a number of preprocessing and signal component identification analysis procedures that need to be carried out prior to classification. Moreover, given the vast amount of information that can be derived from the ECG records, several methodologies have been, and continue to be proposed to try to correlate successfully, ECG signal deviations from the standard pattern to specific arrhythmia conditions (Table 1).

Thus, in general, there are three main processes involved in arrhythmia classifications procedures: ECG signal preprocessing, ECG wave component detection and classification.

1.1.1. ECG signal preprocessing

Since real ECG signals are noisy (i.e. white and mains noise) and contaminated with artefacts (i.e. electromyographic signals due to breathing and chest movement) the first step generally consists of bandpass filtering the measured signals. The choice of overall bandpass filter bandwidth as initial stage is a compromise; it should allow baseline (isoelectric) correction as well as noise reduction without losing high-frequency details that may be critical for individual wave identification [13]. The use of a wavelet denoising operation, prior to feature extraction, has been shown to preserve the sharp features of the ECG signal [14]. For instance, Chen et al. [15] use a wavelet denoising stage based on a discrete wavelet transform, with three levels of decomposition, as the first processing stage for real-time QRS complex detection. Thus a wavelet denoising operation appears to be suitable for on-line operation while maintaining the ECG features for further processing stages.

1.1.2. ECG feature extraction based on wavelet transform operations

The next step in ECG arrhythmia classification consists of identifying individual ECG wave components. Many analysis methods for automatic heartbeat classification have originated from QRS complex signal processing methods [16], because the QRS complex represents the most pronounced characteristic of the ECG signal. One of the techniques that has been favoured to identify individual ECG signal components is the wavelet transform (WT) using a variety of wavelet functions. Amongst the reported wavelet functions used for ECG component identification are the Haar wavelet [17,18], the Mexican hat wavelet [19,20], the Morlet wavelet [21,22] quadratic spline wavelet [23] and combination of wavelet functions [24].

In [13] the authors present a wavelet-based QRS complex detection algorithm on signals contaminated with simulated electromyographic noise which led to a series of results similar to those presented in traditional QRS detection [25,26] techniques. The authors in [27] present the use of the Haar discrete wavelet transform for QRS detection; their algorithm achieved a 95.74% detection accuracy rate on 5 test subject's data records, in comparison with the method presented in [28] which yielded an accuracy of 92.55%.

In [29] the authors use a cubic spline wavelet for detecting the QRS complex which resulted in a mean detection error of 0.75%. In [30], eight 30-min MIT/BIH database records were analyzed using a continuous wavelet transform procedure to detect the characteristic points of the QRS and T waves yielding a 0.47% false detection rate. QRS complex delineation is another type of algorithm aimed at

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