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Time-Domain ECG Signal Analysis Based on Smart-Phone

Shijie Zhou, Zichen Zhang, *Student Member, IEEE*, Jason Gu, *Senior Member, IEEE*

Abstract—In this paper, a time domain algorithm architecture is presented and implemented on a smart-phone for ECG signal analysis. Using the QRS detection algorithm suggested by Pan-Tompkins and the beat classification method, the heart beats are detected and classified as normal beats and premature ventricular contractions (PVCs). Subsequently, a computationally efficient method is presented to separate ventricular tachycardia (VT) and ventricular fibrillation (VF). This method utilizes Lempel and Ziv complexity analysis combined with K-means algorithm for the coarse-graining process. In addition, a new classification rule is presented to recognize VT and VF in our study. The proposed system provides fairly good performance when applied to the MIT-BIH Database. This algorithm architecture can be efficiently used on the mobile platform.

I. INTRODUCTION

CARDIOVASCULAR disease (CVD) is the major threatening disease as well as a leading cause of mortality and premature death in the world. Since people are more concerned about their health, they strive to achieve a healthier lifestyle. Recently, the focus of modern medicine has been shifted from disease diagnosis to disease prevention and control services. ECG signal analysis based on a smart-phone has become a hot area in e-health application to improve patient care and access in public health system. Researchers proposed lots of detection and classification methods based on a mobile platform to support the healthcare and prevent the CVD. In ECG signal analysis, QRS complex is the most remarkable waveform for cardiac event detection, which has high potential amplitude, steep slope (R-wave) and wide duration. These features can be extracted as characteristic quantity, and as a quantized standard in the analysis process. Four main types of algorithms have been used in classifying these detected QRS complex [1-2]:

1) *Time-domain analysis;*
2) *Wavelet transform analysis;*
3) *Syntax analysis;*
4) *Neural network analysis;*

However, most of the presented algorithms were tested against their own database rather than a standard database. This makes the results difficult to be compared and evaluated. And some of the papers focused mostly on different complex algorithm architecture and didn't address the details of the performance of the algorithm they used. Among those algorithms mentioned above, some can improve the detection and classification accuracy immensely, such as wavelet transform [3], neural network analysis [4], syntax analysis [5], Genetic Algorithms [6], Hilbert transform [7], Mathematical Morphology Method [8], etc. However, they generally have huge computation overhead, more resource consumption and less operation efficiency.

In order to improve practicality, we propose combinatorial algorithm architecture of time-domain in our work, which shows the capability to be implemented on a smart-phone. This algorithm architecture is fast and computationally effective using the smart-phone for detection and classification of ECG signal, which includes two mature algorithms (Pan-Tompkins [9] algorithm and Lempel and Ziv (LZ) complexity measure [10]) separately represented by previous research in ECG signal analysis. The combinatorial algorithm is adopted to help create smaller and more cost efficient ECG signal analysis system based on a smart-phone. It is tested against a standard database to make the end result universal and easy to compare and reproduce. In addition, for a real-time application, an ECG signal may contain mixed arrhythmias, e.g. 2 second VT followed by 2 second VF. Few works have taken this into consideration before. We are presenting a new classification rule to recognize ventricular tachycardia (VT) and ventricular fibrillation (VF) from a continuous and mixed ECG signal in our study. Specifically, in the LZ complexity measure part, K-Means algorithm was first used in the coarse-graining process to obtain a better result in VT and VF separation.

The rest of the paper is organized as follows. Section 2 outlines the algorithm architecture and proposed a new classification rule. Section 3 presents the implementations and results. Conclusions and future work are explained in Section 4.

II. ALGORITHM ARCHITECTURE

As to the aspect of ECG analysis algorithm, this work applies the QRS detection algorithm suggested by Pan-Tompkins [9] and the beat classification method described in [11] to detect and classify the beats into normal beats or premature ventricular contraction (PVC). Subsequently, a computationally efficient method is presented to detect VT or VF using complexity analysis proposed by Lempel and Ziv [10]. Fig.1 shows the whole algorithm architecture of the proposed system. Both these two

Shijie Zhou is with the Department of Electrical and Computer, Dalhousie University, Halifax, NS B3J 2X4, Canada (e-mail: shijiezhou@dal.ca).
Zichen Zhang is with the Department of Electrical and Computer, Dalhousie University, Halifax, NS B3J 2X4, Canada (e-mail: zichen.zhang@dal.ca).
Jason Gu is with Electronic & Information Engineering College, Henan University of Science and Technology, Henan, China and also the School of Biomedical Engineering, and the Department of Electrical and Computer, Dalhousie University, Halifax, NS B3J 2X4, Canada (corresponding author to provide phone: 1-902-494-3163; e-mail: Jason.Gu@dal.ca)

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algorithms are based on time domain analysis, which run faster than the algorithms based on frequency domain analysis, wavelet transform or neural network. They are more suitable in real-time applications for recent mobile platform because of the relatively limited computational capabilities.

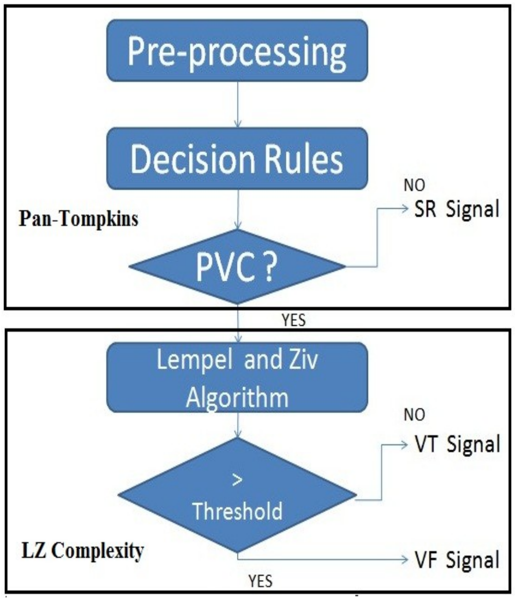

Fig. 1 The architecture of the proposed system

A. Pre-processing Stage

Pre-processing in this case refers to applying filters to remove all the noise and artifacts, which may manifest with similar morphologies as the QRS complex (the main segment in the ECG waveform). As the ECG signal is quasi-periodic, its frequency can be quantified by applying spectral analysis methods [12]. ECG monitors work in different modes in terms of filters for signal processing. The most common settings are monitoring mode and diagnostic mode [13].

Monitoring mode has a filter with a pass-band of 0.5-40 Hz [13]. The filter is used to narrow the bandwidth in an attempt to reduce the contaminants from baseline drift, muscle movement, power line interference, and electrode contact noise. Diagnostic mode monitors the ST-segment and the frequency range of the filter is 0.05-100 Hz [13].

The typical band of frequency for VT and VF is below 12 Hz [16]. The sinus rhythm (SR) signal has a wider frequency band, but mostly below 20 Hz [14]. As there is no need for monitoring the ST-segment and the frequency range is below 40 Hz, our system should work in the monitoring mode. Here a 0.6-22 Hz band-pass filter is used, to maximize the energy of the signal that is of interest (SR, VT and VF).

B. Beat Detection

Beat detection is the basis of any ECG analysis algorithm. It is done by detecting the QRS complex. The algorithm proposed by Pan-Tompkins [9] has been extensively used in beat detection. It is computationally efficient and accurate, reported to have a sensitivity of 99.69% and positive predictivity of 99.77% [9].

C. ECG Classification

Ventricular tachycardia (VT) is a fast heart rhythm originating in the ventricles, which is potentially life-threatening. For the patient who has the clinical criteria for VT, the heart rate is normally over 100 beats per minute [12]. When it exists in a younger healthier heart, it may still work at a life-sustaining level. When it exists in an older frailer heart, it can be fatal [12]. In some cases, VT may degenerate into ventricular fibrillation (VF). VF is a sudden lethal arrhythmia, since the blood cannot be pumped to the body and brain. Medical assistance is required immediately, since death may occur in less than 3 minutes [15]. If timely treatment is conveyed to the patient, VT and VF can be converted to SR, which is a normal rhythm. VT and VF manifest different morphologies. VT is quasi-periodic and VF is a complex chaotic state. Since VT and VF possess different nonlinear physiological characteristics, they should show some difference in their complexity. In [16], the Lempel and Ziv (LZ) complexity analysis was applied to ECG analysis.

1) Band-pass Filter

Before the coarse-graining process, the band-pass filter is used to reduce the influence of baseline wander, different types of noise, and so on. Integer filter is used in our work to reduce the computational cost [12]. The sample rate is 200 samples/second. The cut-off frequency of the high-pass filter is 0.6 Hz, corresponding to a delay of 127.5 samples. And the cut-off frequency 22 Hz for the low-pass filter corresponds to a delay of 2 samples.

2) Coarse-graining Process

Before applying this algorithm, the ECG signal should be translated into a symbolic sequence, normally a binary string. This is called a coarse-graining process. With a selected window length (8 seconds segment), the finite original signal is transformed into a binary sequence. To obtain a better result, k-mean algorithm had been presented in [17-18].

3) LZ Complexity Analysis

After the coarse-graining process, the LZ complexity analysis is applied to count the new sub-sequence of consecutive binary sequence from left to right in the given binary sequence. A detailed description as well as the flow diagram of LZ complexity algorithm has been explained in [19].

D. Classification Rule

In this ECG tele-monitoring system, the signal analysis is performed in the following steps. Firstly, the ECG signal is classified into different rhythms by the Pan-Tompkins algorithm. More specifically, when a beat is detected it is classified as a normal beat, or a PVC. PVC represents any beat of ventricular origin, including VT, VF and some other rhythms. If a beat is classified as a normal beat, the system proceeds to analyze the next beat; if classified as a PVC, this beat will be further analyzed. The ECG may contain different rhythms and those rhythms may mix together, which makes the classification more difficult, since the LZ complexity analysis needs data of at least 1 window length long, which is 8 seconds in our case. Some decision rules are added to the classification step. Three consecutive PVC beats in a row are considered to be an indication of the beginning of VT rhythms (suggested in paper [12]), at which point the following samples will be saved until up to 1600 samples are reached. To increase the reliability of the system, the heart rate is also monitored, which may help improve the accuracy of the analysis algorithm. The number of beats in the saved 1600 samples (8 seconds) can be obtained subsequently. If no more than 80% of the beats belong to the SR, the 1600 samples will be classified as a segment of VT or VF signal, depending on the value of $C(n)$; otherwise, the samples are considered as a SR segment. The $C(n)$ denoted the normalized output of LZ complexity analysis instead of $c(n)$, where the $c(n)$ is increased by one when a new subsequence of consecutive binary sequence is encountered in the scanning process.

III. IMPLEMENTATION AND RESULTS

The algorithm has been implemented both in Carbide C++ emulator and a Nokia S60 smart-phone. It runs well on the Nokia smart phone platform (Fig. 2).

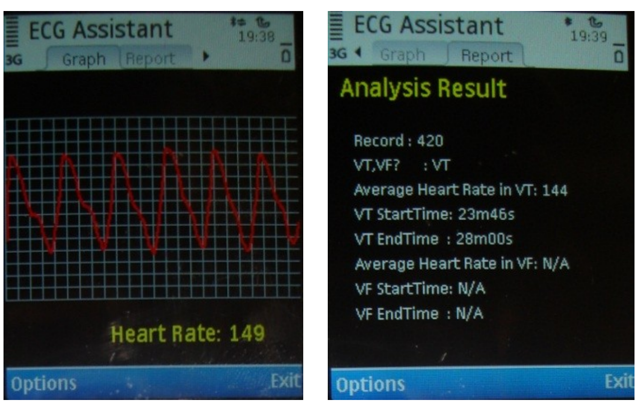

Fig. 2 The algorithm has been tested in a smart-phone with Nokia S60 SDK

In order to provide a general and comparable result, the *MIT-BIH Database* is adopted for both development and evaluation stages [14]. It offers a set of standard ECG records that are open to the public and has been enormously helpful for developing and testing ECG analysis algorithms. Every record contains a continuous recording of ECG signal from a single subject. Most of the records have been annotated by the cardiologist and put into standard annotation files. Note that, the "*MIT-BIH Database*" is actually a database library, which is comprised of various databases, for specific uses. The VT has two types which are monomorphic and polymorphic. Therefore, it is very difficult to distinguish VT from VF; causing the main error in previous studies. For each selected window length in our testing, 196 monomorphic VT segments and 114 VF segments obtained from the Malignant Arrhythmia subset of MIT-BIH are used for both development and evaluation stages.

TABLE I
PERFORMANCE OF THE CLASSIFICATION ALGORITHM

Window Length (sec)	SENSITIVITY SR	VT	VF
10	100/100=100%	91/98= 92.86%	42/57=84.69%
9	100/100=100%	93/98= 94.90%	51/57=89.47%
8	100/100=100%	95/98= 96.94%	54/57=94.74%
7	100/100=100%	93/98= 94.90%	50/57=87.72%
6	100/100=100%	93/98= 94.90%	48/57=84.21%
5	100/100=100%	88/98= 93.62%	48/57=84.21%

TABLE II
RESULTS OF TESTING THE ECG ANALYZER SOFTWARE WITH SELECTED RECORD

Record Name	RHYTHMS CONTAINED IN THE RECORD: The standard annotation	Results of our system
100	No VT and VF	Normal Rhythm
101	No VT and VF	Normal Rhythm
103	No VT and VF	Normal Rhythm
112	No VT and VF	Normal Rhythm
113	No VT and VF	Normal Rhythm
115	No VT and VF	Normal Rhythm
420	VT [23m50s to 28m46s]	VT [22m06s to 23m31s]
422	VT [22m12s to 25m28s]	VT [22m06s to 23m31s]
	VF [25m35s to 34m23s]	VF [23m32s to 30m14s]
611	VT [19m56s to 35m00s]	VT [20m00s to 34m52s]

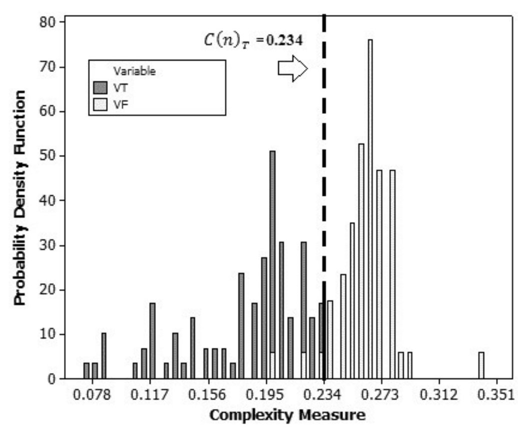

Fig.3.The probability density functions of $C(n)$ for the VT and VF records, selected for development stage

There are 98 VT segments and 57 VF segments from the database for development stage, separately, and the sampling frequency was set to 200 Hz. Computing the results at different window lengths, the best sensitivity is achieved at the 8 seconds window length (Table I). Let C(n) denote the normalized output of LZ complexity algorithm. We obtained

C(n) for all the segments and then used statistical tools to analyze those C(n)s. By examining the probability density function (PDF) which is shown in Fig. 3, a threshold for distinguishing between VT and VF is found, that is $C(n)_T = 0.257696$The signal is considered to be VT, if its C(n) is less than $C(n)_T$, otherwise, it is classified as VF.

In the testing stage, we selected 100 SR segments, 98 VT segments and 57 VF segments from the MIT-BIH Database. The proposed method is applied and the result is shown in Table I. It achieves fairly high performance when the selected window length is 8 seconds. The results show a 100% sensitivity on SR signal, 96.94% sensitivity on VT and 94.74% sensitivity on VF. Some records were chosen from the database to test these decision rules. According to the test results shown in Table II, the ECG analyzer program can correctly detect the cardiac health status of the subject. Table II illustrates that the algorithm architecture with the new classification rule can correctly detect the cardiac health status of the subject.

IV. CONCLUSIONS AND FUTURE WORK

In our study, we have been mainly focusing on the architecture of time domain algorithm, which is simple and computationally efficient. For beat detection, the Pan-Tompkins algorithm is applied and an algorithm based on complexity measure is used for classifying different types of arrhythmias. In addition, the k-means algorithm was addressed to refine the raw signal in coarse-graining process which yields much better performance of classification in the LZ complexity analysis. In order to obtain a comparable and generalized result, the algorithms have been developed and tested on the *MIT-BIH Database*. The proposed algorithm is proven to have a good performance. For classification of arrhythmias, some additional decision rules have been presented. Finally, the algorithm architecture, tested on a smart-phone, obtained a good performance level for detection and classification of ECG signal.

For the future work, this algorithm architecture can be utilized on different mobile platforms for e-health application, which performs on-line ECG beat detection and classification, and then generates an analyzed summary of cardiac health, and automatically sends an alarm message to Emergency when the irregular heart rhythms of high risk are classified. Meanwhile, to provide stable monitoring while the patient is in motion, body movement activity recognition should be investigated. Also, it will have the potential to be used by the hospital as it is both mobile and lightweight, to replace those stationary and expensive ECG machines in most hospitals. Eventually, there will be a natural fusion of this algorithm architecture with other algorithms of bio-signal detection, such as an acceleration monitor, a blood-pressure monitor and a weight monitor, which will detect various types of bio-signals to prevent the sub-health state.

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