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A Portable Real-time ECG Recognition System Based on Smartphone*

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Abstract—**This paper proposed an smartphone-based real-time ECG monitoring and recognition system. The ECG signal was acquired by a MSP430FG4618 low-power microprocessor and was converted via a Bluetooth module for wireless transmission to a smartphone. A noise-tolerant ECG heartbeat recognition algorithm based on discrete wavelet transform and higher-order statistics was employed to identify different types of heartbeats. This system achieved a high accuracy of 98.34 % in identifying seven heartbeat types, which was demonstrated to outperform other studies in the literature. The heartbeat types were recognized in real-time; only 78 ms was required to identify a heartbeat. The portability, real-time processing, and high recognition rate of the system demonstrate the efficiency and effectiveness of the device as a practical computer-aided diagnosis (CAD) system.**

I. Introduction

In recent years, the mortality of cardiovascular disease has always been on top of the list, thus effective diagnosis and treatment of these diseases has become a major issue in the hospital. The first step in diagnosing cardiovascular diseases usually depends on the recording and analysis of electrocardiogram (ECG), which measures the electrical activity of the cardiac conduction system. However, ECG measurement usually requires the patients to carry a device, e.g. a Holter, for more than 24 hours and record the signal. The recorded ECG signals are then brought back to the hospital to be examined by the physicians. This process would take a long period of time and some mistakes or ignorance of minor signs could be made. These issues give rise to the requisite of portable ECG recording and recognition system.

Portable ECG products are not common in the medical market. The reason is expensiveness. Therefore, if the terminal device could be replaced by consumer electronics that are possessed by a great portion of common people, the cost of the device can be extensively lowered. According to the publication of International Telecommunication Union in January 2011 [1], the global mobile phone users have exceeded 50 billion people. Moreover, the International Data market share has been as high as 39.5% in 2011 and expected that it will grow to 45% in 2015. The report indicates there will be more and more users have Android mobile devices.

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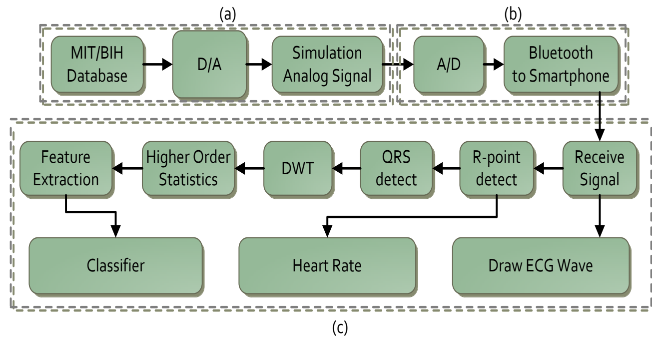


Figure 1. The architecture of the proposed system. (a) Generation of simulated ECG signals; (b) analog to digital conversion (A/D) and Bluetooth transmission; (c) ECG signal monitoring and processing with smartphone.

Android is an open platform which enables the developer to take advantages of the many features provided by the platform to build novel applications. Several attempts have been made to develop portable ECG devices based on Android mobile devices. For example, the two companies Polar and Zephyr have developed an Android platform compatible Bluetooth heartbeat belt. The ECG signal and the calculated heart rate are transmitted to the Android phone by Bluetooth. However, previous research usually focused on ECG and heart rate monitoring, yet lack the capability of arrhythmia detection and diagnosis.

Therefore, we propose to integrate wireless ECG transmutation, heart rate monitoring, and real-time arrhythmia recognition in an Android smartphone. The objective was to build a convenient and effective portable computer-aided diagnosis (CAD) system.

II. Method

The architecture of the proposed system is depicted in Fig. 1. This system is divided into three functional blocks, namely (a) generation of simulated ECG signals; (b) analog to digital conversion (A/D) and Bluetooth transmission; (c) ECG signal monitoring and processing with smartphone, each of which will be described separately in the following sections.

A. Generation of Simulated ECG Signals

A virtual instrument built with LabVIEW program and NI DAQmx input/output device was developed to generate simulated ECG signals for the experiments. The ECG signals were extracted from the MIT/BIH arrhythmia database. By programming an analog output with the data files and setting the sampling rate as 360 Hz, simulated ECG signals based on the real data were generated for testing the performance of the system.

B. Analog to Digital Conversion (A/D) and Bluetooth Transmission

A microcontroller MSP430FG4618 (Texas Instruments Co., Ltd., America) was selected to convert the analog signal to digital [7]. The MSP430 family is designed for low cost, low power consumption embedded applications, which is particularly well suited for developing battery-powered portable device. The controller provides 12-bit A/D converters that would be sufficient for ECG signal acquisition. Since MSP430FG4618 only accepts voltage ranging between 0 V and 2.5 V, signals were boosted by +1.5V using LM358-OP (Texas Instruments Co., Ltd., America) to avoid possible aliasing or saturation.

The HC-05 chip (Wavesen Co., Ltd., China) was used to convert the RS232 serial output from MSP430FG4618 to Bluetooth 2.0 format. HC-05 is characterized as convenient, low-power, and low-cost [3]. It replaced RS232 to communication wirelessly between the MSP430FG4618 and the smartphone.

D. R-point Detection

A median filter with appropriate window size was firstly used eliminate the baseline wander in the ECG signal. Then, the Pan and Tompkins algorithm [4] was used to locate the R points of the heartbeats. Once the R points were located, 64-point QRS segments centered at R point were extracted from the record for the calculation of features for each heartbeats.

E. Feature Calculation

The feature sets play a major role in the effectiveness of a classifier. We have previously applied higher-order statistics (or cumulant) and simple RR-interval features to characterize ECG signals for heartbeat type recognition and successfully implemented a noise-tolerant ECG classifier on a desk-top computer [5]. The application of higher order statistics for characterizing signals has been shown to be effective in suppressing the influence of a wide range of noises and artifacts [5]. In this study, we adopted the same ideas with minor modification and intended to fulfill the classifier on a smartphone with Android platform. The challenges would be the high speed requirement of a real-time system and the much lower computational speed of the smartphone when compared to a desk-top computer.

With each R point in the ECG signal, a 64-point QRS segment centered at the R point was extracted. A five-level DWT was used to decompose the segment into different subband components. Higher-order (2^{nd}, 3^{rd}, and 4^{th}) cumulants were calculated based on the components. For clarity, the j^{th} order cumulant of the D_i subband was denoted as C_{ij} where $i \in \{3, 4, 5\}$ and $j \in \{2, 3, 4\}$. Four sets of cumulant-related features and three RR interval-related features were recruited in this study [6][11]. These features are explained separately as follows.

1. Standard Deviation of the Cumulant (CSD): the standard deviation of the cumulant is defined as:

$$\sigma_{ij} = \sqrt{\frac{1}{2L}\sum_{l=-L}^{L}[c_{ij}(l) - \overline{c_{ij}}]^2} \tag{1}$$

   $i \in \{3, 4, 5\}$ and $j \in \{2, 3, 4\}$, where $\bar{c}_{ij}$ is the sample mean of the cumulant and l is the time shift ranging from –L to +L.

2. Normalized Summation (NS): the normalized summation is defined as the sum of cumulants divides the sum of the absolute cumulant, such that $i \in \{3, 4, 5\}$ and $j \in \{2, 3, 4\}$.

$$NS_{ij} = \sum_{l=-L}^{L} c_{ij}(l) \Big/ \sum_{l=-L}^{L} \left|c_{ij}(l)\right| \tag{2}$$

3. Number of Zero-Crossings (NZC): The number of zero-crossing is important in characterizing the variation of a signal. Since the D_5 subband was observed to show distinct zero-crossing features among different beat types, we focused on the three higher-order cumulants of D_5, i.e. C_{52}, C_{53}, and C_{54}.

4. Symmetry (SYM): The.symmetry is defined as:

$$SYM_{ij} = \sum_{l=1}^{L} \left|c_{ij}(l) - c_{ij}(-l)\right| \Big/ \sum_{l=-L}^{L} \left|c_{ij}(l)\right| \tag{3}$$

   $i \in \{3, 4, 5\}$ and $j \in \{3, 4\}$. Since the Symmetry of the 2^{nd} cumulant is zero, we only need to extract from the 3^{rd} and 4^{th} cumulants.

5. RR Interval-related Features: The RR interval is defined as difference in the time between two adjacent R peaks. We extracted three RR interval-related features, including the instantaneous RR interval, the ratio between the instantaneous and the previous ones, and the ratio between the previous and the one before it.

In summary, the feature vector contains 30 features, including nine CSDs, nine NSs, three NZCs, six SYMs, and three RR interval-related features. Each feature was normalized by subtracting the mean value from the feature and dividing by the feature's standard deviation. This process intended to normalize all the features to the same level.

F. Classification

The back propagation neural network (BPNN) is a multi-layer perceptron (MLP) [8] which has been proven to be suitable for use in the classification of nonlinear data. The typical BPNN consists of three layers, including an input layer, a hidden layer, and an output layer. Hyperbolic tangent sigmoid function is used as activation function and the weights between neurons of consecutive layers are modified by back propagating the error signals backwardly layer by layer to approach optimal solution. The number of neurons in the hidden layer would affect the nonlinearity of the neural classifier, and is empirically chosen as sixty. The training phase of the classifier was done on a desk-top computer and the optimal weights were saved and downloaded onto the smartphone for the classifier in the testing phase of the real-time classifier.

G. *Android Platform*

There are two reasons for choosing Android platform in the study. First, Android is an open source platform that based on the Java of Linux core system and the Android SDK provides the tools and APIs necessary to begin developing applications on the Android platform. Second, Android smartphone has successfully gained a significant market share in recent years. In this study, we used HTC Incredible S. The phone has CPU 1GHz, 768MB RAM and runs the version 2.3.2 of Android operational system [9].

The flow chart of the functions on the smartphone is depicted in Fig. 2. First of all, the Bluetooth function on the smartphone must be turn on, which then searches for the nearby device for connection. Once connected, the smartphone begins to receive the raw ECG data transmitted from the HC-05 chip and display on the screen. The received data was processed in a five-second basis. The R points were first located and the feature sets and heart rates were calculated. The features were fed into the trained BPNN classifier and the results were displayed on the screen. The raw data, heart rate, and ECG type were saved to the SD card.

III. Results and Discussions

The first step in using this system was connecting the smartphone to the Bluetooth data transmission. A Bluetooth connecting interface was developed. After touching the button on the smartphone, three functional keys appear on the screen (Fig. 3 (a)). Touching the "Make discoverable" key enables the smartphone to search for nearby Bluetooth devices. After touching the "Connect a device" key, the names of these devices are shown on the screen (Fig. 3 (b)). Select a device and the smartphone would try to connect to it through Bluetooth. If Bluetooth is connected successfully, the received ECG data are shown on the screen. If the connection failed, the system would show an alarm sign of "Not connected and request for another connection.

The graphic user interface (GUI) includes the display of ECG waveform, heart rate, and recognized beat type, as depicted in Fig. 4. The heart rate was calculated from the inverse of the averaged five consecutive RR-intervals, intending to reduce the heart rate errors caused by false detection of R peaks. The waveform was displayed and processed in a 5-sec basis and the average time to classify a beat type was 78 ms.

To evaluate the performance of the system in ECG recognition, fifteen records (100, 105, 106, 109, 111, 114, 116, 118, 119, 124, 200, 207,209, 212, 214) were selected from the MIT / BIH arrhythmia database [10]. The performance of the system was measured by the recognition rates of individual beat types and the average accuracy.

With the analog ECG signals simulated by the virtual instrument built with LabVIEW program and NI DAQmx input/output device, the recognition rates of the portable real-time ECG beat recognition system were calculated and summarized in Table I. An impressively high average

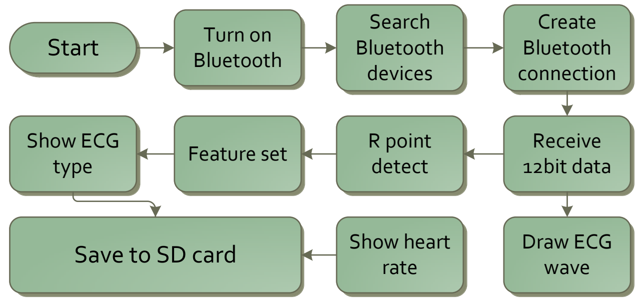
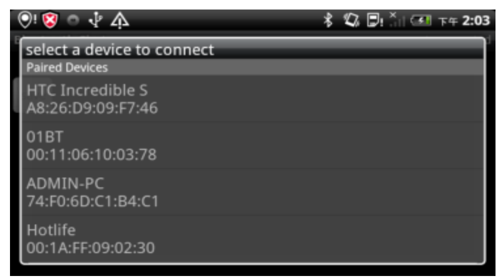


Figure 2. Flow chart of the programs on the smartphone.

(a)



(b)

Figure 3. (a) Bluetooth make discoverable and (b)connect a device process.

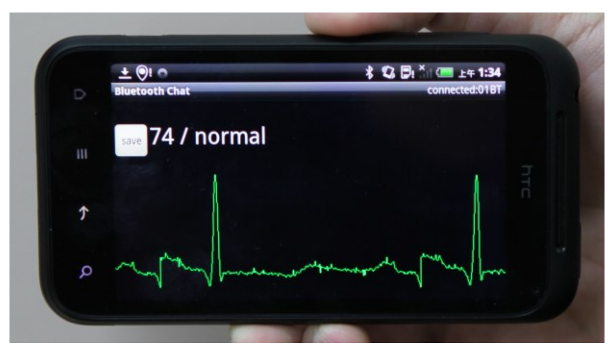


Figure 4. Graphic user interface on the smartphone.

TABLE I. Classification results using BPNN

ECG beat type	*Recognition rate (%)*
NORMAL	98.98
LBBB	98.58
RBBB	97.62
PVC	97.70
APB	88.29
VEB	93.27
VFW	92.68
Average accuracy	98.34

accuracy of 98.34 % was achieved. It is noticeable that the recognition rates were high across different beat types. The lowest rate of 88.29 % was associated with Atrial premature Beats (APB). Referring to our other studies [11], the recognition rates of APB were usually among the lowest. The requirement of real-time and accurately detecting the R-points for calculating effective features further deteriorated the results. This may be improved by modifying the R-point detection algorithm and adding more APB samples in the training phase of the classifier.

It is also interesting to compare the performance of the proposed method to that of other studies. Three effective methods [12-14] were selected for comparison. The comparative results are summarized in Table II. The high average accuracy of the proposed method outperforms the other three methods in discriminating the highest number (seven) of beat types when compared to five in [13] and four in [14]. The results in Tables 1 and 2 support the effectiveness of using the proposed method in a smartphone to discriminate ECG arrhythmias in real-time.

The quick classification and high accuracy of the system demonstrated the feasibility of the system as an effective portable and real-time device for ECG beat recognition.

IV. Conclusion and Future Work

A portable and real-time cardiac arrhythmia recognition system based on smart phone was proposed in the study. The ECG signal was acquired by a MSP430FG4618 controller and transmitted wirelessly through Bluetooth by a HC-05 chip. The signal was received and processed on a smart phone with Android platform. A noise-tolerant algorithm based on wavelet decomposition and higher-order statistics were exploited to identify the heartbeat types. This method was demonstrated to be effective and efficient. High accuracy of 98.34 % was achieved to successfully differentiate seven types of heartbeats with a short average recognition time of 78 ms/beat. The proposed system was demonstrated to outperform other systems published in the literature. The portability and real-time processing capabilities of the system further enhance the clinical value of the system as a computer-aided diagnosis (CAD) device.

This paper shows the prototype of the system. However, this prototype still leaves room for improvement, such as refining the graphic user interface and improving the recognition rate of APB. Furthermore, other physiological parameters, such as temperature, blood pressure, blood oxygen level, etc., could be integrated to build a portable multi-functional health monitoring device with real-time computer-aided diagnosis.

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TABLE II. Comparison of different ECG beat classification methods.

Method	*Number of beat type*	*Accuracy*
FHyb-HOSA [12]	7	96.06 %
MME [13]	5	97.78 %
Neuro-Fuzy [14]	4	98.00 %
This Study	7	98.34 %

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