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Predicting Cardiovascular Disease from Real-Time Electrocardiographic Monitoring: An Adaptive Machine Learning Approach on a Cell Phone

Zhanpeng Jin, *Student Member, IEEE*, Yuwen Sun, and Allen C. Cheng, *Member, IEEE*

***Abstract*—To date, cardiovascular disease (CVD) is the leading cause of global death. The Electrocardiogram (ECG) is the most widely adopted clinical tool that measures the electrical activities of the heart from the body surface. However, heart rhythm irregularities cannot always be detected on a standard resting ECG machine, since they may not occur during an individual's recording session. Common Holter-based portable solutions that record ECG for up to 24 to 48 hours lack the capability to provide real-time feedback. In this research, we seek to establish a cell phone-based real-time monitoring technology for CVD, capable of performing continuous on-line ECG processing, generating a personalized cardiac health summary report in layman's language, automatically detecting and classifying abnormal CVD conditions, all in real time. Specifically, we developed an adaptive artificial neural network (ANN)-based machine learning technique, combining both an individual's cardiac characteristics and information from clinical ECG databases, to train the cell phone to learn to adapt to its user's physiological conditions to achieve better ECG feature extraction and more accurate CVD classification on cell phones.**

I. Introduction

CARDIOVASCULAR disease (CVD), such as heart attack, stroke, and hypertension, is caused by disorders of the heart and blood vessels and by far continues to be the leading cause of death in the world for both developed and developing countries. More than 1.4 million people suffer from angina and 275,000 people have a heart attack annually. Many health institutes have suggested that people with arrhythmias in both emergency and elective settings, should receive timely assessment by an appropriate clinician to ensure accurate diagnosis and effective treatment and rehabilitation [4].

The Electrocardiogram (ECG) is the most widely adopted clinical tool that can measure and record the electrical activity of the heart from the body surface. However, rare or intermittent symptoms can be very easily missed by looking at the ECG snapshot taken by a resting ECG machine if these symptoms do not appear during the (usually brief) recording session. Existing mobile solutions such as Holter monitors can be used to record an individual's ECG data for 24–48 hours, but the diagnostic yields with Holter monitoring are very low (5–13%) [15]. These deficiencies of existing approaches necessitate the need for continuous electrocardiographic monitoring for physiological signs of cardiac abnormality. After an extensive survey of a large variety of commercially available monitoring systems as well as some of the most visible research proposals, we could classify these existing systems into three groups: 1) systems that record signals and perform classification off-line; 2) systems that perform remote real-time classification; and 3) systems that provide local online real-time classification.

Among the first group of systems, the improvement of Holter-based monitors and event recorders stand out, e.g., GE's SEER, Philips's DigiTrack, and Midmark's IQmark. However, these solutions are recording devices: there is no real-time processing of ECG and analysis, if any, is mostly performed off-line. The second group augments the telemedical functionalities via remote real-time monitoring [2][4][7][8][10][13]. Most of them make use of mobile phones or PDAs to collect the ECG data and transmit it to a central monitoring station where the processing of ECG can take place on a PC and classification of CVD, if any, is performed by a clinical expert. The third group includes recent research proposals that can provide some intermediate level of local real-time ECG processing and/or CVD classification by using up-to-date smartphones or PDAs [3][5][12]. While the initial results of these work-in-progress efforts show high promise to reduce the turnaround time, several technological challenges must be addressed before a truly mobile CVD diagnosis solution can be realized.

This research seeks to establish a cell phone-based wearable platform, capable of performing continuous monitoring and recording of ECG in real time, generating an individualized cardio health summary report in layman's language, automatically detecting abnormal CVD conditions and classifying them in real time at any place and anytime. After an extensive literature review, we did not find any work that built a complete ECG monitoring and rhythm classification system in a cell phone using advanced machine learning algorithms. Moreover, most of prior portable solutions proposed rule-based CVD detection or simple clustering techniques, which lack the individual adaptability to provide

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Zhanpeng Jin is with the Department of Electrical and Computer Engineering, University of Pittsburgh, Pittsburgh, PA 15261 USA (phone: 412-624-8897; fax: 412-624-8003, e-mail: zhj6@pitt.edu).

Yuwen Sun is with the Department of Electrical and Computer Engineering, University of Pittsburgh, Pittsburgh, PA 15261 USA (e-mail: yus25@pitt.edu).

Allen C. Cheng is with the Departments of Electrical and Computer Engineering, Bioengineering, Neurological Surgery, and Computer Science, University of Pittsburgh, Pittsburgh, PA 15261 USA (e-mail: acc33@pitt.edu).

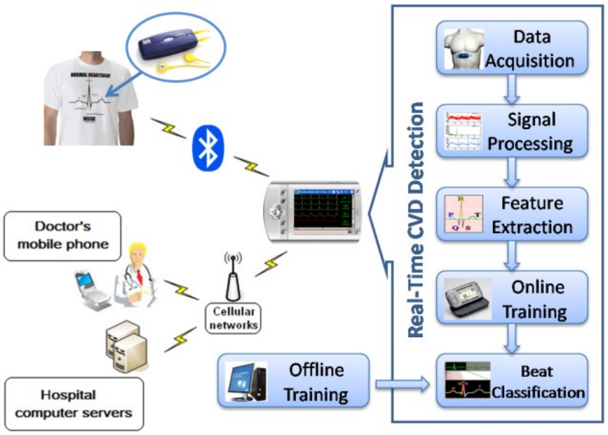

Fig. 1. The workflow of HeartToGo ECG processing platform.

Fig. 2. *HeartToGo* Prototype, including an HTC PDA phone with Microsoft Windows Mobile 6 and a single channel Alive Heart Monitor. Two standard lead configurations: [Upper-right] chest leads with wire connection; [Lower-right] chest leads with snap connectors [1].

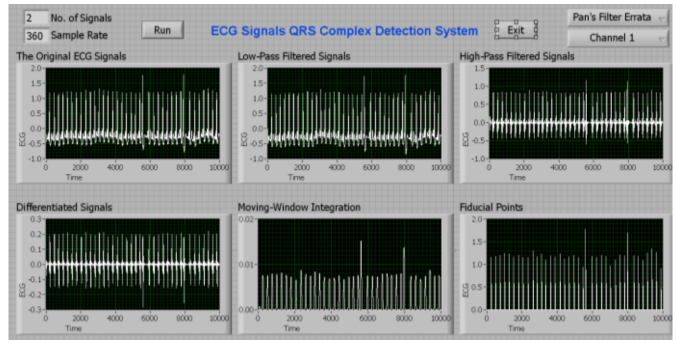

Fig. 3. QRS Complex Detection System for ECG Signals.

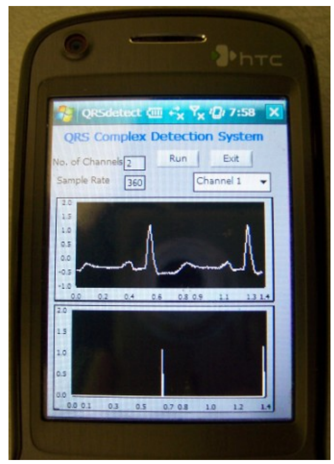

Fig. 4. QRS Complex Detection System: [Top] ECG signal; [Bottom] Identified QRS Complex

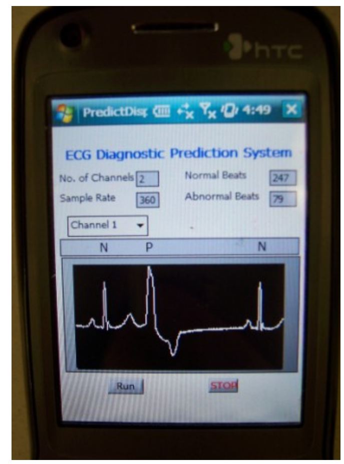

Fig. 5. ECG Diagnostic Predication System: arrhythmia beats are marked above their respective ECG waves.

more accurate assessment. To this end, we focused on making the following contributions in this project: 1) we constructed *HeartToGo* – a portable physical prototype including an off-the-shelf wireless heart monitor, Bluetooth, MATLAB/ LabVIEW simulation environment capable of not only collecting, recording, transmit-ting, and displaying ECG data in real time, but also analyzing the acquired ECG data and detecting cardiac abnormities; 2) we designed a machine learning based CVD diagnosis module and proposing an adaptive artificial neural network (ANN) based hybrid strategy combing patient-specific training methods and established medical database training methods.

II. System Design Framework

In this section, we explain the process that we followed (as shown in Fig. 1) and its corresponding system design in order to construct a wearable and portable ECG diagnostic platform that can generate comparable results similar to a standard resting ECG machine.

A. Data Acquisition

First, we had to select an appropriate ECG source from which the data used in the following experiments could be extracted and processed. To demonstrate the adaptability of our proposed design and facilitate an objective comparison with other state-of-the-art ECG processing techniques, we report our results based on both real-time ECG signals and existing ECG databases.

To acquire real-time ECG signals, we employed Alive Technology's state-of-the-art wireless ECG and heart monitor (Fig.2) [1], which is a light-weight (60g), low-power (60 hours of operation with continuous wireless transmission) wearable single channel ECG sensing device capable of recording 300 8-bit samples per second. It is equipped with a class 1 Bluetooth transmitter, with a range of up to 100 meters, which can send its data to cell phones or other wireless devices. The connection between Alive's monitor and cell phone was established via Bluetooth and the data was acquired in our LabVIEW implementation via a Serial Port Profile (SPP).

In order to verify the proper functionality and accuracy of the proposed system, we also emulated the real-time data of heart activities and reported the results with a PC based on the most widely used MIT-BIH Arrhythmia Database [9]. The MIT-BIH database contains 48 30-min ambulatory ECG recordings. The original data files were directly stored in the cell phone and a specific signal exporter was developed to convert the original "format 212" of MIT-BIH database to a binary format readable by LabVIEW.

B. ECG Feature Extraction

The classical Pan-Tompkins QRS Detection Algorithm [11] and its following errata which we adopted and implemented in our ECG diagnosis and analysis system are proved to have a

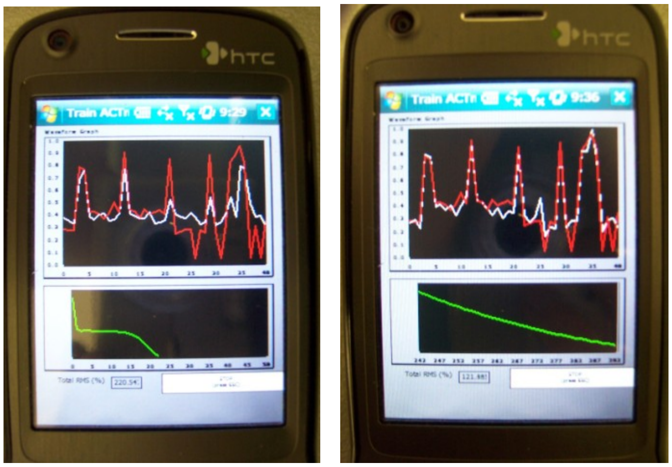

Fig. 6. Two training phases of ANN implemented on the Cell Phone. [Top] Red – the target results, White – the predicted results; [Bottom] Green – the Root Mean Square (RMS) error, which was continuously decreased as the training progressed.

sensitivity of 99.69% and positive prediction of 99.77% when evaluated with the MIT/BIH arrhythmia database.

The QRS detection algorithm consists of a band-pass filtering stage that uses a set of cascaded filters. The first two stages consist of a low-pass filter with a cut-off frequency at about 11Hz and a gain of 36 with a filtering processing delay of 6 samples, and a high-pass filter with a cut-off frequency of about 5Hz with a unity gain and a processing delay of 16 samples. The derivative stage differentiates signals to obtain information about the slope of the QRSs. The squaring stage identifies the slope of the frequency response curve of the derivative and restricts false positives caused by T waves with higher spectral energy. The moving-window integration stage is used to obtain waveform feature information in addition to the information about the slope and the width of the QRS complex. Finally, the rising edge of the integration waveform corresponds to the desired QRS complex. A fiducial mark for the QRS complex feature can be represented by the temporal location of the peak of R wave, which is determined according to the waveform excerpt located within the range of this rising edge. As detailed above, our implementation of this 6-stage QRS complex detection framework was illustrated in Fig. 3, which could successfully reduce the effects of irregular distance between peaks, irregular peak forms, and the presence of a low-frequency component in ECG due to patient's breathing. Also, our cell phone implementation of this fast feature extraction algorithm is illustrated in Fig. 4. As part of this work-in-progress, we have extended the diagnosis capability to include additional features such as the RR interval, the QRS width, the R peak, and the beat width.

C. MLP ANN-Based ECG Classification

Among the numerous paradigms of ANN, we focus on a model called the feed forward multilayer perceptron (MLP) neural network, which is one of the best-known techniques used in pattern recognition and classification, time-series modeling, nonlinear control, and system identification. In this study, we exploit potential applications of the MLP structure

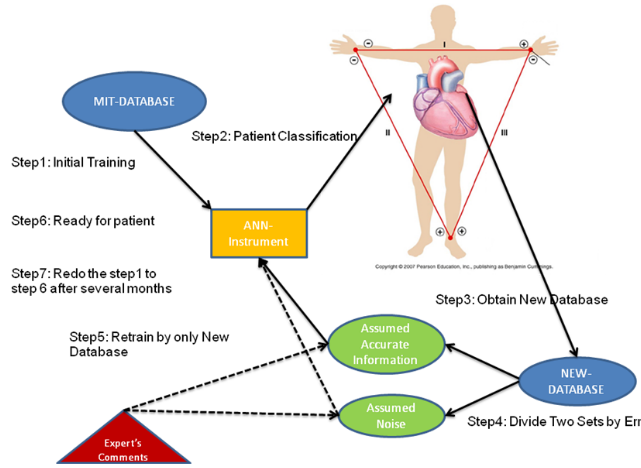

Fig. 7. Adaptive Patient Specific ECG Predication Diagram.

to perform an important ECG processing task: QRS beat pattern classification, on a state-of-the-art smartphone.

QRS beat classification is a crucial task in ECG diagnosis and current methods highly rely on various features extracted or measured from the ECG waveform. Although many sophisticated feature extraction techniques have been proposed, we need to explore the most efficient algorithms with acceptable accuracy due to the relatively limited computation and battery budget of contemporary cell phone.

In this study, we used the morphologies of the heartbeats rather than the cardiac inter-beat intervals to detect cardiac abnormalities and identify potential arrhythmia. Given the QRS complex and fiducial information obtained from the feature extraction stage, the input to the MLP ANN is the original QRS beat pattern with appropriate linear amplitude scaling. Each output is associated with a particular class of arrhythmia conditions. Each input template contains 51 samples centered on the annotated fiducial mark in the recording, which approximately represents a time segment of 150 ms. Fig. 6 presents two different training phases of our ANN implementation on the cell phone, from which we could observe the converged fitting effect.

D. Adaptive ANN-Based Prediction

Compared to traditional approaches, patient-specific classification approaches analyze the ECG waveform characteristics more precisely on a patient-by-patient basis. Nevertheless, real-time applications often require faster training techniques or methods that can be applied to the detector in advance. Thus, we proposed a hybrid adaptive strategy that utilizes both patient-specific information and established ECG medical databases, and is more suitable for the real-time mobile environment.

As shown in Fig. 7, the entire training process we proposed can be described as follows: 1) using an established ECG database to train the ANN; 2) testing the trained ANN on a patient; 3) collecting a new ECG data set M from this patient; 4) dividing this new data set M into two groups, named A and B, whose testing errors are respectively within or beyond the

TABLE I
DISTRIBUTION OF SAMPLES IN EACH PARTITION

	No. of Beats	Trial A	Trial B	Trial C
Normal	1856	600	600	656
RBBB	1781	450	550	781
PVC	99	25	30	44
PACE	1685	450	550	685
PFUS	30	7	11	12
Total	5421	1532	1741	2178

TABLE II
PREDICATION ACCURACY OF NORMAL AND 4 ABNORMAL BEATS (UNIT: %)

Train	A		B		C		Average
Test	B	C	A	C	A	B	
Normal	99.7	100	99.7	95.5	99.5	100	99
RBBB	98.2	98.7	97.8	98.6	97.2	97.6	98
PVC	93.3	93.2	88.0	95.5	92.0	93.3	92.6
PACE	96.4	97.1	95.6	96.4	95.3	95.5	96
PFUS	81.8	83.3	71.4	91.7	85.7	72.7	81

* RBBB=Right bundle branch block beat; PVC=Premature ventricular contraction; PACE=Paced beat; PFUS=Fusion of paced and normal beat.

pre-determined threshold; 5) retraining the ANN based on the data set M combining with expert's annotation or purely based on the data set A; 6) the individualized ANN can perform more accurate CVD assessment by accounting for physiological characteristics that are specific to the patient. Starting from a generic ECG processing structure and following this adaptive training process, the proposed ANN will be able to classify patients' individual ECG data more accurately.

The final user interface of the proposed CVD classification and prediction framework is shown in Fig. 5, where each beat is classified into the normal set or one of 13 arrhythmias and the associated type is shown above it. In this snapshot, two "N" markers correspond to the normal beats and a Premature Ventricular Contraction (PVC) is identified as a "P".

III. PROTOTYPES AND RESULTS

Our HeartToGo prototype consists of an Alive™ Bluetooth ECG and Heart Monitor, a Microsoft Windows Mobile™ cell phone. MATLAB™ was utilized to develop and verify our ECG processing and CVD classification algorithms. A LabVIEW™-based platform was developed to deploy the verified algorithms onto the smartphone to assess the real-time performance in the target mobile environment.

In this study, we investigated 5,421 QRS complex templates which cover the normal beats and four arrhythmia conditions from the MIT-BIH arrhythmia database. To estimate the classification rate accurately, we adopted the three-way cross-validation method that is designed to minimize the variations due to the random sampling of finite-size data samples [6]. We partitioned each class of the data set randomly into three disjoint subsets of approximately equal size denoted by, Trial A, Trial B, and Trail C. The training and testing was performed three times each with each one of the three subsets as the training set and the other two as the testing sets. We did such partitioning using MATLAB and the details are summarized in Table 1.

We performed the experiments in which a 51-30-5 MLP ANN structure was used to classify all beats into five classes. Table 2 summarizes the results. The total predication accuracy achieves more than 90% except the slightly smaller accuracy of PFUS, which is still better than an acceptable level.

IV. CONCLUSION

In this article, we proposed *HeartToGo* - a cell phone-based wearable platform capable of performing continuous monitoring and recording of ECG data in real time, generating individualized cardio health summary reports in layman's language, and automatically detecting abnormal CVD conditions by identifying abnormal ECG signals at any place and anytime. We have developed the experimental prototype and demonstrated the on-phone processing of the ECG for the feature identification and classification of heartbeats. We are working on co-advancing ECG-based CVD diagnostic algorithms and application-specific embedded hardware and software to make the best use of, as well as to push, the computation and energy budget of a cell phone to realize a broader CVD detection in real-time.

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