# Real-time Personalized Cardiac Arrhythmia Detection and Diagnosis: A Cloud Computing Architecture

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***Abstract*— Cardiac arrhythmia is one of the most popular heart diseases that could lead to serious consequences. However, it is difficult for traditional electrocardiography (ECG) devices to capture arrhythmia symptoms during patients' hospital visits due to their intermittent occurrence nature. A few researchers recently propose continuous monitoring systems to address this problem. However, there are some practical issues which may hamper the system from being widely used, such as low efficiency, offline data acquisition and processing, and high energy consumption. To account for these challenges, in this paper, we develop a new cloud computing based architecture for real-time personalized cardiac arrhythmia detection and diagnosis. In order to reduce energy consumption on patients' mobile devices and enable realtime data processing, we outsource the computationally complex tasks to the cloud while having the lightweight tasks processed locally. The proposed online learning algorithms facilitate a personalized system. Moreover, we adopt clinical criteria for arrhythmia classification, which better prepares our system for practical use than previous systems. Simulations with data from the MIT-BIH database validate the efficiency and efficacy of our system.**

## I. INTRODUCTION

Cardiac arrhythmias are a group of conditions in which the heartbeat is irregular. Mild arrhythmias have symptoms like lightheadedness, shortness of breath, chest pain, or passing out. Some serious arrhythmias may lead to strokes, heart failure or even sudden death. Atrial fibrillation and atrial flutter resulted in 112,000 deaths in 2013, up from 29,000 in 1990 [1]. Nevertheless, it is difficult to identify arrhythmia symptoms from a traditional electrocardiograph (ECG) during a routine physical exam or during an exam in the hospital emergency room due to its intermittent occurrence nature. Therefore, continuous monitoring of patients' heartbeats in daily life is crucial to arrhythmia detection and diagnosis.

Currently, many researchers and companies have proposed a number of healthcare systems or schemes that focus on this issue. Unfortunately, the large-scale implementation of available monitoring systems and schemes is deterred by multiple factors. First, most existing systems are inefficient in practical implementation [2]. Some systems cannot provide online diagnosis; and others rely heavily on having the patient data sent directly to a monitoring team for review. Some other systems [3], [4] restrict patients' mobility because of the use of personal computers. Second, to realize online automated diagnosis, some systems and schemes [5] require all the ECG data to be sent to a remote health center, which highly relies on the network. When the network is congested or the connection is lost, the system is down and cannot provide any service. Third, the performance of arrhythmia classification is easily affected by the significant variations of ECG signals from different patients [6]. Fourth, most of the previous systems have a tedious initialization phase because of the use of offline training [7]–[9], which take extraordinary time before it can be used in practice.

In this paper, we introduce a cloud computing based personalized system for real-time cardiac arrhythmia detection and diagnosis. With our system, a patient who has cardiac arrhythmia disease will experience efficient detection and online diagnosis of arrhythmia events using real-time monitoring of the ECG signal. Specifically, we propose an online cardiac arrhythmia detection and a personalized online diagnosis framework. We combine a genetic algorithm, an online backpropagation algorithm, and a boosting algorithm in the classification stage to improve the arrhythmia classification accuracy. The online arrhythmia detection is done locally on the patient's smart phone, and the computationally intensive classification is processed in a remote cloud, which saves a lot of computation energy for the smart phone. Moreover, since we adopt online learning algorithms, the initialization phase is processed in real-time and can be personalized. In addition, we adopt clinical criteria for arrhythmia classification, which better prepares our system for practical use than previous systems.

### A. Related Work and Challenges

*1) Online Arrhythmia Detection:* Online abnormal heartbeat detection has increasingly become a popular task among researchers and companies. Although some existing algorithms claim to achieve high accuracies, they still suffer from high false alarm rates [7], [8], [10]. For instance, in previous work [8], the detection operation relies on a Recursive AutoRegressive (RAR) modeling [11], which, however, has a high false alarm rate. How to increase the detection accuracy and decrease the false alarm rate is a very challenging problem.

*2) Online Arrhythmia Classification:* Artificial neural networks (ANNs) are powerful tools for pattern recognition as they are capable of learning complex, nonlinear tasks, and this capability can be key for ECG beat recognition and classification [9]. Although many ANN-based schemes for ECG waveform classification have demonstrated good performance [12]–[14], there are still some issues that hamper

This work was partially supported by the U.S. National Science Foundation under grants CNS-1602172 and CNS-1566479.

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978-1-5090-4179-4/17/$31.00 ©2017 IEEE

their practical implementations. First, the accuracy is easily affected by the significant variability of ECG signals from different patients [6]. For example, some healthy athletics have a regular heartbeat rate around 60 beats per minute, but this heartbeat activity is normally considered as a sinus bradycardia for ordinary people. In this case, the normal heart state can be incorrectly identified as an abnormality. Second, offline training is another barrier for the implementation of the previous algorithms. The offline training schemes require a pre-collected data set for the classifier training purposes, where the data set has to include enough activity types for the classifier to learn over the complete set of possible states. Even if we considered the personalization problem mentioned above and were willing to use the personalized data, it is inefficient to collect large amounts of personalized ECG data from all types of activities, which will results in a long initialization phase. Therefore, how to design an efficient and effective online arrhythmia classification scheme is an open and challenging issue.

## II. System Architecture

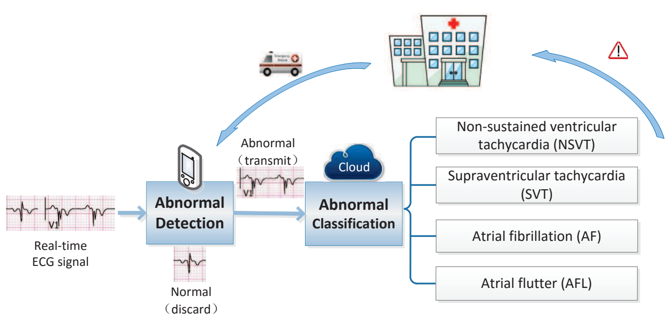


Fig. 1. The architecture of the proposed real-time personalized cardiac arrhythmia detection and diagnosis system.

As shown in Fig. 1, we propose a personalized healthcare system for real-time cardiac arrhythmia detection and diagnosis. In particular, real-time ECG signals collected by sponsors are first transmitted to the smart phone carried by the patient. After performing the arrhythmia detection scheme, the mobile phone outsources the abnormal ECG signals to the cloud, where the arrhythmia classification is conducted. The intuition of this system design is as follows. As the system continuously collects ECG signals, transmitting all the collected signals to the cloud for detection and classification would incur huge amounts of energy consumption and transmission time at the smart phone. By conducting the abnormal detection scheme at the smart phone, we can filter out the normal signals and only outsource the abnormal ones to the cloud, which can significantly save a lot of energy and reduce the transmission time at the smart phone. In addition, as classifying the abnormal ECG signals into different types of arrhythmias on mobile devices is prohibitively difficult due to their limited computational capability, outsourcing this task to the cloud can relieve the burden on mobile devices and perform the classification much more efficiently.

The arrhythmia classification criteria we adopt is the same as that used in hospitals [15]. Specifically, in out of all types of arrhythmias, physicians are most interested in 4 types, namely Non-sustained ventricular tachycardia (NSVT), Supraventricular tachycardia (SVT), Atrial fibrillation (AF), and Atrial flutter (AFL). Generally, continuous occurrences of these four types of arrhythmias may lead to life-threatening situations like sudden death or stroke. Therefore, patients with those arrhythmias need to be sent to the hospital for immediate treatment. Thus, if such an emergency situation is identified, the cloud will send an alert together with the current ECG segment to the hospital. Physicians at the hospital will immediately review the ECG signals and the corresponding classification result. If it is indeed an emergency, the physician will contact the patient to provide an immediate remote treatment or to dispatch an ambulance immediately.

## III. System Description

In this section, we describe the three main components of the proposed system, i.e., online arrhythmia detection, and online arrhythmia classification, as well as personalized system design, respectively.

### A. Online Arrhythmia Detection

Our main idea is to detect arrhythmias by using a Recursive AutoRegressive (RAR) algorithm [11]. In particular, the RAR algorithm performs one-step ahead prediction about the next sample in the ECG waveform. If arrhythmias occur, the prediction of the RAR model will be very different from the real sample. As a result, the monitoring and examination of the residual of the prediction, i.e., prediction error, can enable arrhythmia detection. After analyzing other types of arrhythmia incidents' residuals, we find that the peaks of the residuals, the peak intervals, and the mean of the residuals all reveal arrhythmias. Therefore, we consider the variance, median and mean of the residuals as well as the R-peak interval ratio of the ECG signal as the detection metrics. Here, the interval ratio is the ratio of the current R-peak interval to the average interval that is periodically updated.

In most previous works like [8], a set of fixed thresholds are set for the variance, median, and mean of the residual. An abnormal incident is detected once any of the thresholds is exceeded. However, with the dynamic heart rate in different activities, a lot of normal heartbeats could be possibly detected as arrhythmias, resulting in many false alarms. In our proposed algorithm, thresholds are updated periodically based on the recent data so that we can reduce the number of false alarms. The threshold is updated by $Threshold = \mu + 5 \cdot \sigma$, where $\mu$ is the mean and $\sigma$ is the variance of most recent data.

Once an arrhythmia is detected, the ECG data of the current heartbeat is transmitted to the cloud for classification, which is described in the following.

### B. Online Arrhythmia Classification

The most common artificial neural network (ANN) for classification is the multi-layer perceptron neural network (MLPNN), a feedforward ANN. Since the architecture of the network influences the classification performance, we propose to first employ a genetic algorithm (GA) along with an online back propagation (BP) algorithm to train and select top 15 networks with optimal classification accuracy. Then, we leverage an online boosting algorithm to efficiently combine these 15 classifiers (ANNs) and get a stronger classifier. In so doing, we can get more accurate classification results more efficiently compared with traditional algorithms that only use one typical artificial neural network.

Besides, before feeding into the MLPNN, we need to extract features from the original data. For each heartbeat, we extract both the morphological and temporal features for arrhythmia classification. Specifically, we adopt the discrete wavelet transform (DWT) for morphological feature extraction, and then process the morphological features by employing the principal component analysis (PCA) so as to reduce the dimensionality and thus significantly improve the efficiency of the training for an ANN classifier. Nine principal components are extracted after the process, which contain about $95\%$ of the overall energy in the original features. Besides the morphological features, we also need to extract the temporal feature extraction. Most previous works like [8] use two intervals, the current peak-to-peak interval $R_{j-1}R_j$ and the next interval $R_jR_{j+1}$. However, it may not be able to capture the features of arrhythmias accurately. For example, when a life-threatening PVC incident occurs, the current RR-interval and the next RR-interval are similar as the PVC begins, which cannot reflect the change of the heart situation. Therefore, we utilize the time-length ratio of the current RR-interval to the average RR-intervals to better capture the feature. The average RR-interval calculated in the current period is updated periodically.

The reason why we use an "online" BP algorithm for the training process and an "online" boosting algorithm for strengthening the classifier is that an online algorithm has low computation complexity and hence is much more efficient, which enables real-time training. Compared with offline training methods, an online training algorithm uses only one training sample in each iteration to train the classifiers and then discard it after training. In other words, we do not need to wait for the whole training data sets to train the classifier. The classifier is available to be used after each training iteration.

### C. Personalized System Design

We have shown above how to perform online arrhythmia detection and arrhythmia classification. However, the detection and classification processes should be customized for each patient, since different individuals' ECGs have different characteristics. In this section, we enable a personalized system by having a two-phase training process as presented in Fig. 2. The universal training phase is to obtain an universal model. Based on the MIT-BIH database which contains healthy heartbeats, we can obtain a Recursive AutoRegressive model $RAR(n_y, \lambda)$ for the arrhythmia detection. Similarly, the arrhythmia classifiers are trained by using the MIT-Arrythmia database which contains all the arrhythmia types. The personalized training phase starts after a patient wearing the ECG sensors. The online arrhythmia detection process is activated to mark each beat as either a normal beat or an abnormal beat. The normal beats are sent directly to the cloud server as personalized normal data for online personalized training purposes, and the abnormal beats are sent to the physicians for manual labeling. The labeled arrhythmia beats are then also sent to the cloud server for online personalized training. After this initialization phase, our system can automatically detect and diagnose cardiac arrhythmias in real-time.

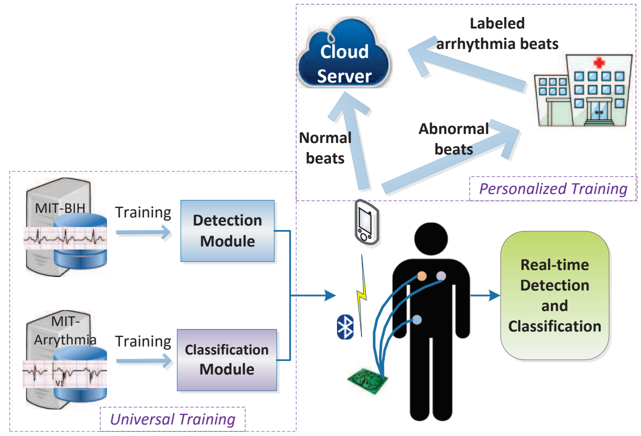


Fig. 2. Two-phase personalized system design.

In addition, to better adapt to the patient's health status, the personalized training can be carried out periodically depending on the treatment plan made by physicians, and the period can be adjustable.

## IV. System Evaluation

We evaluate our algorithms by conducting simulations with data from the MIT-BIH Arrhythmia Database [16] and focus on NSVT arrhythmia classification. As discussed in Section III-C, the purpose of the universal training phase is to get 15 ANNs with optimal structures by employing a genetic algorithm. In each ANN there are two potential hidden layers with 0 to 31 possible neurons at each layer. The population is set to 200. Evolution from one generation to the next is carried out by the online BP algorithm. After 20 generations, we obtain top 15 ANNs and then put them into the online boosting algorithm for the personalized training phase. We only show three experiment results in Table I. Classification accuracy is defined as the ratio of the number of correctly classified heartbeats to the total number of heartbeats. The testing data is collected from user's personal data containing half normal and half arrhythmia heartbeats. We compare the classification accuracy under three situations. Take record 223 for instance. In the first situation, classifiers are only engaged in the universal training phase where the training data set consists of the same number of normal and arrhythmia heartbeats collected from records 106, 114, 119, 201, 203, 205, 210, and 215. The classification accuracy is $94.33\%$. In the second and third situation, classifiers are trained through both the universal and the personalized

TABLE I

CLASSIFICATION ACCURACY WITH TWO-PHASE TRAINING.

| Record | 1st phase universal training | 2nd phase personalized training | Classification accuracy |
|---|---|---|---|
| 203 | 106,114,119,201, 205,210,215,223 | - | 83.23% |
| 203 | 106,114,119,201, 205,210,215,223 | 203(n) | 85.14% |
| 203 | 106,114,119,201, 205,210,215,223 | 203(n+a) | 86.63% |
| 205 | 106,114,119,201, 203,210,215,223 | - | 92.24% |
| 205 | 106,114,119,201, 203,210,215,223 | 205(n) | 94.87% |
| 205 | 106,114,119,201, 203,210,215,223 | 205(n+a) | 95.32% |
| 223 | 106,114,119,201, 203,205,210,215 | - | 94.33% |
| 223 | 106,114,119,201, 203,205,210,215 | 223(n) | 96.04% |
| 223 | 106,114,119,201, 203,205,210,215 | 223(n+a) | 97.32% |

training phases. 223(n) denotes user 223's personal normal heartbeats. 223(n+a) represents a data set containing user 223's normal and arrhythmia heartbeats. The classification accuracy increases to 96.04% and 97.32% in the second and the third situations, respectively. Classification results illustrate that the personalized training phase improves classification accuracy, and personalized arrhythmia data makes the system even more accurate.

To further demonstrate how our algorithms work in the real scenarios, we develop an Android app on a Google Nexus 6 smart phone. We implement only online arrhythmia detection algorithm in this application, and the app sends the abnormal beats to a remote cloud for arrhythmia classification. The cloud server we use is Linode (1 CPU, 1GB RAM, Ubuntu 14.04 LTS operating system), a privately owned virtual server provider. The implemented algorithm in the cloud server receives data from the patient's smart phone, and sends necessary feedbacks and alerts to the smart phone and/or the hospital.

In the following, we present experiment results in terms of power consumption and system latency to illustrate the efficiency and efficacy of the system. Specifically, we evaluate our system with records selected from the MIT-BIH database and measure the energy consumption (obtained by an Android App called PowerTutor [17]) of the smart phone in this process. The average power consumed by the smart phone to process and transmit 30-minute ECG signals is 20.8 Joules(J) and 24.3J using Wi-Fi and LTE connection, respectively. Compared with the smart phone screen's power consumption for 30 minutes, which is 3200J, our system energy consumption is extremely low[1]. The total processing time for analyzing 30-minute's data is 77,961 ms on average. By comparison, we collect the same data when the detection and classification are both executed locally on the smart phone. For this scheme, the average energy consumption is 172J, and the average total processing time is 267,233ms. Apparently, our proposed scheme can significantly reduce the energy consumption and processing time, and is capable of performing real-time arrhythmia detection and classification.

## V. CONCLUSIONS

In this paper, we have presented an innovative personalized cardiac arrhythmia detection and diagnosis system, which consists of a lightweight online arrhythmia detection algorithm and an online arrhythmia classification algorithm. We have also further developed the system to make it personalized. In addition, we have implemented the system by designing an Android App, and utilizing the cloud environment. The simulation and experiment results have illustrated that the system has low energy consumption and is capable of real-time arrhythmia detection and diagnosis, which shows great potential for future smart health device development.

[1]The built-in battery monitor in Android system shows that for 1h17m42s at maximum brightness, the screen costs 640mAh. Since the working voltage for Nexus 6 is around 3.6V, we can get that the screen's energy consumption for 1h17m42s is about 8294J, and hence that for 30 minutes is about 3200J.

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