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Issues in Implementing a Knowledge-based ECG Analyzer for Personal Mobile Health Monitoring

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Abstract— **Advances in sensor technology, personal mobile devices, and wireless broadband communications are enabling the development of an integrated personal mobile health monitoring system that can provide patients with a useful tool to assess their own health and manage their personal health information anytime and anywhere. Personal mobile devices, such as PDAs and mobile phones, are becoming more powerful integrated information management tools and play a major role in many people's lives. We focus on designing a health-monitoring system for people who suffer from cardiac arrhythmias. We have developed computer simulation models to evaluate the performance of appropriate electrocardiogram (ECG) analysis techniques that can be implemented on personal mobile devices. This paper describes an ECG analyzer to perform ECG beat and episode detection and classification. We have obtained promising preliminary results from our study. Also, we discuss several key considerations when implementing a mobile health monitoring solution. The mobile ECG analyzer would become a front-end patient health data acquisition module, which is connected to the Personal Health Information Management System (PHIMS) for data repository.**

I. INTRODUCTION

ECG is the electrical manifestation of the contractile activity of the heart's myocardium. The P, QRS and T waves characterise the ECG waveform. The most prominent feature is the QRS complex, where R denotes the peak of QRS complex. The ECG remains the most common non-invasive method for diagnosing heart diseases. Any disturbance in the regular rhythmic activity of the heart (amplitude, duration and shape of rhythms) is known as arrhythmia. Cardiac arrhythmia can be defined as an irregular single heartbeat (arrhythmic beat) or a deviating group of heartbeats (arrhythmic episode) in the rate, regularity, and source or conduction of the cardiac electric impulse, which may lead to severe consequences. Cardiac arrhythmias may cause the heart to pump less effectively, causing insufficient blood to reach the brain and other vital organs. When the body's blood flow is inadequate, the person can faint or suffer chest pain. Sometimes, sudden cardiac death can occur. In general, cardiac arrhythmias can be classified into two categories. The first category is life-threatening and requires immediate medical attention, which includes ventricular fibrillation and tachycardia. Our focus is to detect these arrhythmias automatically [1-5]. The second category includes arrhythmias that are not life-threatening but may require medications to prevent further deterioration.

ECG is a low-cost, non-invasive test for cardiac monitoring, which has become the common diagnostic tool. Certain cardiac arrhythmias occur occasionally and up to a few days of ECG recording may be required using a Holter monitor in order to capture these beats and episodes. However, Holter monitors are used to record ECG data only and the analysis is performed offline. Therefore, a continuous cardiac monitoring and online analysis system could detect these rare episodes of cardiac arrhythmias as they occur. Identifying an arrhythmia requires the classification of heartbeats. The rhythm of the ECG signal can then be determined through the classification of consecutive heartbeats. Classification of heartbeats can be very time-consuming and hence automated processing of the ECG data would serve as a useful clinical tool.

Physicians interpret the features extracted from the ECG waveform and decide whether the heartbeat belongs to the normal (healthy) sinus rhythm or to an appropriate class of arrhythmia. Algorithms have been proposed for developing automated systems to accurately detect and classify the ECG signals in real time [1-7]. The applied method of signal processing techniques can be categorized into statistical, syntactic, or artificial intelligence. They include techniques such as time-frequency analysis, template matching and feature extraction methods. Artificial neural networks (ANN) were employed [4-7] due to their relatively higher recognition ability for ECG beat classification. The key task is to select a simple ECG analysis technique that offers accuracy and efficiency and can be implemented on mobile platforms, such as PDAs and mobile phones.

Monitoring of vital parameters, such as cardiac rhythms, often needs to be conducted over an extensive period of time. Therefore, we have designed our solution with patient mobility in mind to facilitate mobile monitoring [3, 10]. The PHIMS from the University of Washington [8-9] was customized for cardiac care. In a world where people are highly mobile and medical facilities are overloaded, PHIMS could become a platform solution, which enables personalised home-based monitoring via Internet where patients can access their health records anytime and anywhere.

II. VISION

Our proposed system for personal mobile health monitoring requires the implementation of an appropriate ECG analysis technique on a mobile platform. This ECG analyzer has to be simple, accurate and robust in operation. The wireless connectivity structure for home-based patient monitoring is a combination of Bluetooth and wireless local area networks (WLAN) technologies, to support a reasonable mobility range within a typical home environment and reliable wireless Internet connectivity.

Bluetooth is used for short-range wireless connectivity between wearable cardiac sensor module and PDA. Patient information and cardiac data can be managed by a micro PHIMS database on the PDA and wirelessly transferred to the remote PHIMS server via WLAN connection. The medical specialist can access updated patient records via PHIMS server. The envisioned system architecture is shown in Figure 1.

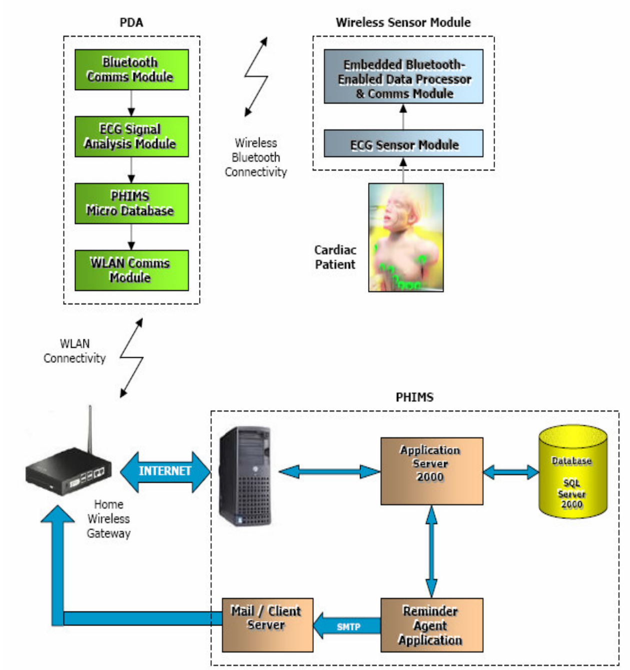

Fig. 1. Envisioned E-Medicine system architecture for cardiac monitoring.

The mobile personal area network (MPAN) is a user-end wireless network for interconnectivity among devices, which consists of an embedded wireless cardiac sensor module, a mobile PDA and a wireless gateway. ECG waveforms are acquired by a Bluetooth-enabled cardiac sensor module and wirelessly transmitted to PDA via serial communications. A patient can manage his/her own personal medical records and ECG data using PHIMS micro database for PDA, which is designed to have a simplified user interface of PHIMS. Information is wirelessly exchanged between PDA and PHIMS via home WLAN.

III. METHODOLOGY

A. *ECG Analyzer*

In this paper, we are investigating the feasibility of the selected ECG analysis technique through computer simulation. A simple and accurate technique for ECG analysis is required for implementation on resource-limited mobile platforms, such as PDA and mobile phones, which would be suitable for home-based mobile monitoring. In previous studies, analysis techniques were mostly based on the analysis of the ECG signal where ECG features were required to be extracted for the arrhythmias detection and classification. However, ECG feature extraction may not always be feasible due to several factors: (a) feature extraction procedure is complicated by the presence of noise and (b) it is resource-intensive and time-consuming, thus impossible for real-time implementation. An alternative is to use only the RR-interval feature for analysis, but it is expected that only limited types of arrhythmias can be detected and classified.

A knowledge-based technique for the classification of cardiac rhythms based only on the RR interval signal was proposed in [1]. The method comprises of four steps (refer to Figure 2): (1) preprocessing of the ECG data, (2) QRS detection and computation of the RR-interval component, (3) arrhythmic beat classification and (4) arrhythmic episode detection and classification. This knowledge-based classifier has a simple structure with only the single RR interval feature required. The preprocessing is based on standard ECG signal processing techniques [2]. The rule-based arrhythmic beat and episode detection and classification [1] were implemented and tested.

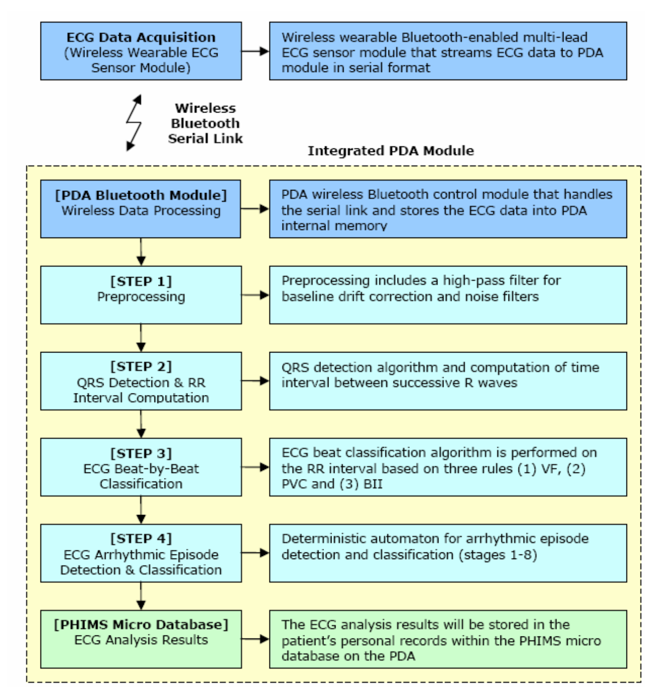

Fig. 2. Flow diagram of an ECG analyzer.

1. ECG Preprocessing and Feature Extraction

The preprocessing follows the standard algorithms in the literature [2, 10]. The ECG data were filtered using a simple highpass filter for baseline drift correction, which would be suitable for PDA implementation (step 1). Next, the QRS locations were determined as the signal peaks were detected based on moving window integrator (MWI) outputs. The method was modified to include a running estimate of the peak locations' intervals in the ECG signal before QRS detection. The detected signal peak of the MWI output was verified against its corresponding maximum peak position in the filtered ECG signal. The use of this variable window size enables R wave locations to be correctly determined, but it is dependent on the current peak interval estimates in the ECG signal. The RR interval was established by measuring the time interval (the number of samples) between successive R peak locations (step 2).

2. Arrhythmic Beat and Episode Classification

In arrhythmic beat classification, beat-by-beat detection was applied using rules provided by medical experts [1], which utilizes the duration of the examined cardiac cycle and that of the previous and next cycles, in a three RR-interval sliding window (step 3). The rules were used to classify the middle RR-interval only. Four different categories of cardiac rhythms were recognized: normal sinus rhythm (NSR), premature ventricular contraction (PVC), ventricular fibrillation (VF), 2nd degree heart block (BII). It was assumed that an ECG beat that does not belong to any of the above arrhythmic categories would be classified as normal.

The results of the beat classification were used to detect and classify arrhythmic episodes (step 4). The algorithm for arrhythmic episode detection and classification is based on a deterministic automaton using expert's knowledge [1]. Six cardiac rhythms could be detected and classified (ventricular bigeminy (VBG), ventricular trigeminy (VTG), ventricular couplet (VC), ventricular tachycardia (VT), ventricular fibrillation (VF), and 2nd degree heart block (BII)). A similar assumption was made where the rhythm would be classified as normal unless an episode belonging to one of the above arrhythmia types was detected and classified. All arrhythmic episodes start with a specified type of classified beat (PVC for ventricular bigeminy, trigeminy, couplets and tachycardia, VF for ventricular fibrillation and BII for 2nd degree heart block) and end with any type of classified beat

B. Customized PHIMS/FARMS PC-based Prototype for Cardiac Care and System Design on PDA

In distributed home environments, patients can upload their electronic cardiac data, diagnostic results and other health information recorded and analyzed into a home PC to the remote PHIMS server via Internet. The Facilitated Accurate Referral Management System (FARMS) is a messaging system that interconnects patients, healthcare providers and specialists. Physicians can download the patient's records and diagnostic results for review. A PC-based prototype of PHIMS/FARMS was developed for cardiac care including ECG signal analysis modules.

These days, personal mobile communication and data storage devices are widely used. The concept of PHIMS can be extended to personal mobile health records (PMHR), which provides patient-centered electronic health information in various compatible formats, which can be either accessed remotely through Internet using mobile devices, such as PDA and mobile phones or locally stored in secured data format on mobile devices and portable storage media, such as flashdrives, smartcards and RFIDs.

In our next phase of development, the current PC-based E-medicine web portal will be implemented on PDA platform using the Microsoft .NET platform with C# while the Microsoft SQL server CE is used as a database [8].

IV. RESULTS AND DISCUSSION

In our preliminary testing, calibrated ECG arrhythmia datasets from the electronic vital signs simulator (BioTEK Lionheart) were used to represent annotated ECG data acquired from patients. The datasets were 100 beat samples for each cardiac rhythm type. The knowledge-based classification algorithm was able to detect the NSR, PVC and VF arrhythmic beats with sensitivity of 100%. The specificity for NSR, PVC and VF detection was 100%, 80% and 94%, respectively. At this stage, the simulation results are not conclusive, as we have used calibrated ECG datasets and assumed ideal stationary conditions without external interferences or human movement artifacts. In separate experiments, we have successfully conducted tests on the Bluetooth wireless connectivity in lab environment and mobile conditions. For real implementation on mobile devices, such as PDA, we have listed several considerations as follows:

(1) Accuracy of ECG analyzer: The actual performance of the ECG analyzer is critically dependent on the quality of the preprocessing module. The selected technique [1] is simple as compared to other approaches in the literature since it uses only the RR interval, which can be extracted with good accuracy even in noisy ECG recordings.

(2) External interferences: The wireless health monitoring system is designed to operate in an open mobile environment. Hence, the main concern is its robustness in a dynamic environment of spurious interferences. Bluetooth is a suitable technology for interconnecting the wireless sensor module and PDA. Bluetooth uses interference reduction techniques such as frequency hopping spread spectrum (FHSS) scheme over multiple data channels, error correction schemes, etc. We have conducted a series of interference and mobility tests to determine the performance of Bluetooth using the BioTEK Lionheart simulator linked to a 12-lead ECG module (QRS Universal ECG) that is connected to a paired Bluetooth serial adapter (Initium Promi-SD 101) and wirelessly connected to a laptop. This system is configured for real-time streaming of ECG data wirelessly from the ECG module to a remote laptop with a graphical user interface showing ECG signals from all the 12 leads. The system operates robustly in the lab environment, which contains PCs, WLAN access points, personal mobile phones, lab equipment, etc as interference sources. However, there were slight errors observed occasionally between segments of ECG data (around 10-20% of a single ECG beat). This data loss could be due to Bluetooth's digital data encoding and packetization delays. In the mobility test, we randomly moved the ECG module and simulator within the vicinity of the laptop (around 10-20 m radius). The actual operating range was observed to be around 12 m. This shows that the system is robust to guarantee reliable wireless connectivity within a body area (i.e. sensor to PDA within ~3 m radius). However, there is no automatic reconnection if the sensor and the PDA move out of range. Therefore, a synchronisation protocol should be developed to handle the disconnection between the sensor and the PDA when they are out of operating range. For example, a user alert can be generated or the system can continue to search for the paired device within a time period (e.g. 5-10 minutes) after which the system automatically switches off to conserve power due to limited battery life in mobile devices. The close proximity between different wireless communication protocols that interoperate within patient's body area (e.g., Bluetooth, WLAN or GSM) may induce electromagnetic interferences at the sensor contact points, which may introduce high-energy electrical spikes coupled with the ECG data. However, a control protocol can be developed to regulate the overall dataflow to reduce the possibility of interference. For example, the sensor can be designed to store around 15-20 minutes of ECG data in the buffer such that the wireless data transfer between the sensor and the PDA will take place at intervals instead of doing it continuously. The wireless ports (i.e. WLAN) can be deactivated by default unless the user initiates a remote connection with the PHIMS server for data update or referral request.

(3) Human movement artifacts: For practical usage, human movement artifacts are unavoidable. It is essential to embed an intelligent algorithm to alert the user whenever the sensor is off contact (i.e. no heartbeat detected when the system is on). The program will incorporate ECG analysis module, designed to record abnormal data and stored it for further analysis. Normal ECG recordings could be discarded.

(4) Wearable user interface: Although a multi-lead ECG sensor is commonly used in standard clinical settings, the number of leads in the ECG sensor module can be further reduced since the arrhythmia classification technique requires only the RR interval component. This enables the simplification of the human interface portion of the ECG sensor module into a single wearable unit (e.g. a wireless compact chest band).

(5) Computational efficiency: The key performance measure for evaluating applications developed for resource-limited mobile devices is computational efficiency. The processing time of the ECG analysis module on a PC (e.g. P4 2 GHz) was estimated to be around 15 minutes for a 30-minute ECG recording. Real-time data processing could be achieved on an advanced PDA with a faster processor.

V. CONCLUSION

In this paper, we have evaluated the performance of a knowledge-based ECG analyzer using only the RR interval parameter with calibrated ECG datasets. In the discussion, we have listed some of the key potential challenges and suggested several solutions for the implementation on mobile platforms. This system is designed to be a personal cardiac health screening tool that can be integrated with the PHIMS/FARMS system to promote distributed diagnosis and home healthcare.

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