PORTABLE HEART ATTACK WARNING SYSTEM BY MONITORING THE ST SEGMENT VIA SMARTPHONE ELECTROCARDIOGRAM PROCESSING

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Cardiovascular disease (CVD) is the single leading cause of death in both developed and developing countries. The most deadly CVD is heart attack, which 7,900,000 Americans suffer each year, and 16% of cases are fatal. The Electrocardiogram (ECG) is the most widely adopted clinical tool to diagnose and assess the risk of CVD. Early diagnosis of heart attacks, by detecting abnormal ST segments within one hour of the onset of symptoms, is necessary for successful treatment. In clinical settings, resting ECGs are used to monitor patients automatically. However, given the sporadic nature of heart attacks, it is unlikely that the patient will be in a clinical setting at the onset of a heart attack. While Holter-based portable monitoring solutions offer 24 to 48-hour ECG recording, they lack the capability of providing any real-time feedback for the thousands of heart beats they record, which must be tediously analyzed offline.

Processing ECG signals on a smartphone-based platform would unite the portability of Holter monitors and the real-time processing capability of state-of-the-art resting ECG machines to provide an assistive diagnosis for early heart attack warning. Furthermore, smartphones serve as an ideal platform for telemedicine and alert systems and have a portable form factor. To detect heart attacks via ECG processing, a real-time, accurate, context aware ST segment monitoring algorithm, based on principal component analysis and a support vector machine classifier is proposed and evaluated. Real-time feedback is provided by implementing a state-of-the-art,

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multilevel warning system ranging from audible notifications to text messages to points of contacts with the GPS location of the user. The smartphone test bed makes use of a novel, real-time verification system using a streaming database to analyze the strain of heart attack detection system under normal phone operation. Furthermore, the entire system is prototyped and fully functional, running on a smartphone to demonstrate the real-time, portable functionality of the platform. Experimental results show that a classification accuracy of 96% for ST segment elevation of individual beats can be achieved and all ST episodes were correctly detected during testing with the European ST database.

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- CHD: Coronary heart disease

- CVD: Cardiovascular disease

- ECG: Electrocardiogram (also EKG)

- EOF: End of file

- MI: Myocardial infarction (heart attack)

- PCA: Principal component analysis

- PCI: Percutaneous coronary intervention

- POC: Point of contact

- STEMI: ST elevation heart myocardial infarction

- SVM: Support vector machine

PREFACE

The author would like to thank Shimeng Huang, Yuwen Sun, Zhanpeng Jin, Jun Cheng, Heather

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1.0   INTRODUCTION

With the advent of computers, technology is playing an ever increasing role in society by making jobs easier and faster, providing new medians for communications, and most importantly, increasing quality of life with medical devices. Through the twentieth century, medical devices have helped save lives. One example of a life-changing innovation is the electrocardiogram (ECG), which allows physicians to monitor the heart via its electrical activity. Furthermore, there has been an increasing trend to make medical devices smaller and more portable, to allow the patient to use them at all times. Examples of such devices are pacemakers, portable respirators, and automated external defibrillators. More recently, newer, more powerful smartphones, which are becoming increasingly popular, can also serve as platforms for health-related conditions; diabetes patients can keep track of their insulin levels, sleep quality can be monitored, and diet and exercise statistics can be calculated all using smartphones. With a form factor that is designed for portability, powerful computing abilities, and their built-in communication interfaces, smartphones make an ideal platform for portable, real-time assistive medical diagnosis.

A new direction for smartphone assistive diagnosis is monitoring the body's internal signals for changes in a user's health that are life-threatening. The goal of this research is to provide portable, real-time heart attack detection via smartphone ECG processing. For users, such a device would serve as an additional layer of heart attack detection, aside from the

conventional warning signs, such as chest pain. Furthermore, acute heart attacks sometimes leave victims with little-to-no warning signs. By continuously monitoring the heart's ECG, heart attacks that could be previously undetectable by users may be able to be detected before damage occurs.

1.1   MOTIVATION

Cardiovascular disease (CVD) is the single leading cause of death in both developed and developing countries. According to the American Heart Association, in the United States alone 80,000,000 people are estimated to have one or more forms of CVD and nearly 2,400 Americans die of CVD each day. The most deadly CVD is heart attack, which 7,900,000 Americans suffer each year, and 16% of cases (1,200,000) are fatal [1]. Furthermore, some 300,000 Americans a year suffer sudden cardiac death, an event generally defined as death resulting from coronary heart disease (CHD), which usually leads to heart attack, within an hour of the onset of symptoms [2].

The Electrocardiogram (ECG) is the most widely adopted clinical tool to diagnose and assess the risk of CVD. Approximately seventy percent of heart attacks are detectable in the ECG; the remaining thirty percent are not recognizable due to various reasons such as small infarctions, multiple infarctions, and electrocardiography is an indirect method [3]. Early diagnosis of acute heart attacks, within one hour of the onset of symptoms [4], is necessary for successful treatment, including percutaneous coronary intervention (PCI) and for the timely administration of thrombolytic therapy.

In clinical settings, resting ECGs are used to monitor patients automatically, along with physicians performing diagnosis by reading the ECG. However, abnormalities may not be detected on standard resting ECG machines since the condition may not be present at that moment in time. Furthermore, it is unlikely that the patient will be in a clinical setting at the onset of the heart attack due to their sporadic nature. While Holter-based portable monitoring solutions offer 24 to 48-hour ECG recording, they lack the capability of providing any real-time feedback for the thousands of heart beats they record, which must be tediously analyzed offline. In the case of acute MI, Holter monitors are not an effective diagnosis tool because they simply record the heart's activity and provide no assistive diagnosis or warnings.

Processing ECG signals on a smartphone-based platform would unite the portability of Holter monitors and the real-time processing capability of state-of-the-art resting ECG machines to provide an assistive diagnosis for early heart attack warning. Furthermore, smartphones serve as an ideal platform for a telemedicine and alert system and have a portable form factor.

1.2   GOALS

Currently, there are two options for monitoring the heart though ECGs: the rest ECG machine found in clinical settings and the portable Holter monitor. Neither platform is well-suited for detecting heart attacks. Patients are unlikely to be connected to a resting ECG machine when having a heart attack and Holter monitors provide recordings of the heart's activity in time, instead of real-time feedback and heart attack detection.

The goal of this research is to combine the powerful, accurate heart attack detection processing features of resting ECG machines with the portability of Holter monitors by

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processing the ECG on a smartphone. Furthermore, the communication features of the smartphone will be used to provide a tiered level of warnings for the user and a point-of-contact (POC), including pop-up messages, audible alerts, text messages, and GPS location, should a heart attack be detected. Moreover, to make the system practical, it must not interfere with the normal multitasking workloads of the smartphone, such as voice, video, and music.

1.3   CONTRIBUTIONS

As previously stated, this research proposes the smartphone as a portable platform for heart attack alert that is capable of providing the real-time feedback of resting ECG machines and the portability of Holter monitors. To accomplish this, a real-time, accurate, context aware ST segment monitoring algorithm, based on PCA and a SVM classifier, for the detection of ST elevation heart attacks was proposed and verified. Furthermore, a state-of-the-art heart attack warning system to provide the user with a multilayered system of warnings was proposed and implemented. Another contribution is to propose and implement a real-time verification system for ECG processing on a smartphone using a streaming database to analyze the strain of heart attack detection system under normal phone operation. Finally, the entire system is constructed and demonstrates the real-time, portable functionality of the system on the target smartphone platform.

1.4 SYSTEM OVERVIEW

This thesis implements a heart attack detection and warning system on a smartphone by real-time ECG processing. To obtain the user's ECG (and accelerometer data), a wearable sensor is used. This sensor communicates with the smartphone using the Bluetooth protocol. The smartphone then displays the ECG in real time and at various zoom levels using a custom-written, multi-threaded C# application named *HeartToGo*. To process the ECG for heart attack detection, the proposed accurate, real-time, context aware principal component analysis (PCA) / support vector machine (SVM) algorithm is used. Feature extraction consists of heartbeat detection, segmentation, down sampling, and PCA. The SVM then classifies the beat as normal or ST elevated in real-time. This algorithm was first prototyped in MATLAB and then implemented on the smartphone.

Should elevated ST beats occur for a duration of at least thirty seconds (to be clinically significant) a multilevel system of warnings will begin. The user will immediately be notified via pop-up, vibratory, and audible alerts and the abnormal ECG will begin being uploaded to a database. If the user does not acknowledge the warning (e.g. experiencing a heart attack) a designated POC will be notified via text message or email that the user could be experiencing a heart attack and has not acknowledged the warning. Furthermore, the user's GPS location will be transmitted to the POC.

Aside from the implementation of the system, another important aspect is real-time testing and verification. The novel test plan method of streaming an expertly annotated database to the phone in place of the sensor is used. Not only does this method provide complete transparency between testing and normal functionally, it allows a very difficult to test situation to simulate, the heart attack, to be tested on the phone. Furthermore, using this testing approach the

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strain caused by the custom ECG processing software on the phone could be analyzed to ensure that real-time deadlines are being met and that normal phone functionality is not hindered.

1.5   THESIS ORGANIZATION

This section provides an introduction to the problem of heart attack detection on a smartphone, thesis goals, contributions, and an overview. The remainder of this work is organized as follows: chapter 2 will provide medical background information on heart attack, electrocardiography, and detecting heart attack with electrocardiography. Chapter 3 will propose the smartphone as a platform for ECG processing and demonstrate this with a state-of-the-art test bed. An accurate, real-time, context aware heart attack detection algorithm will be proposed, implemented, and tested in chapter 4. Next, chapter 5 will introduce the multilayered system of alerts and telemedicine functionalities that have been proposed for heart attack detection on a smartphone. Chapter 6 provides a novel testing and verification procedure by using an expertly annotated database that is streamed to the phone. Chapter 7 provides comments for the system and outlines future work. Finally, chapter 8 provides concluding statements.

2.0 BACKGROUND

Before discussing a heart attack detection algorithm, it is first necessary to introduce the proper biomedical background to understand heart attacks, electrocardiograms, and how to detect a heart attack using an electrocardiogram. Therefore, this chapter provides a brief introduction to the clinical aspects of cardiology.

2.1 HEART ATTACK

Officially known as myocardial infarctions (MIs), heart attacks are the most deadly CVD, which 7,900,000 Americans suffer each year, and 16% of cases (1,200,000) are fatal [1]. Furthermore, some 300,000 Americans a year suffer sudden cardiac death, an event generally defined as death resulting from coronary heart disease (CHD), which usually leads to heart attack, within an hour of the onset of symptoms [2]. Heart attacks occur when the supply of blood to the heart is interrupted, commonly due to the blockage of a coronary artery, which causes heart cells to die. When left untreated, the blockage of blood supply (ischemia) results in the infarction of heart muscle tissue (myocardium). Classic heart attack warning signs include chest/shoulder pain, shortness of breath, nausea, vomiting, and sweating. However, heart attacks frequently occur without any warning signs; these heart attacks are referred to as silent.

There are two types of heart attacks: ST elevation myocardial infarctions (STEMIs) and non-ST segment elevation myocardial infarctions [4]. STEMIs are larger than non STEMIs [5], which this research will focus on. Early diagnosis of acute heart attacks is necessary for successful treatment, including percutaneous coronary intervention (PCI) and for the timely administration of thrombolytic therapy. For successful treatment, it is necessary to diagnose heart attacks within one hour of the onset of symptoms [4].

2.2   ELECTROCARDIOGRAPHY

2.2.1   Electrocardiography basics

The Electrocardiogram (ECG) is the most widely adopted clinical tool to diagnose and assess the risk of CVD. The ECG measures the electrical impulses of the heart via electrodes on the skin's surface. Electrical activity is present because each contraction of the heart is preceded by electrical excitation waves [4]. Figure 1 shows the morphology of a single heartbeat. As shown, a normal heartbeat consists of fluctuations in voltage causing three waves: the P wave, QRS complex, and the T wave. The P wave represents the electrical activity of the right atrium, right atrial activation and initiation, the left atrial activation and initiation, and the left atrium. The QRS complex is due to the electrical forces generated from ventricular depolarization. Repolarization is represented by the T wave. Also, note that the ST segment, central to this research, lies between the end of the QRS complex and the T wave [4]. Between waves the voltage returns to a constant level, referred to as the isoelectric level.
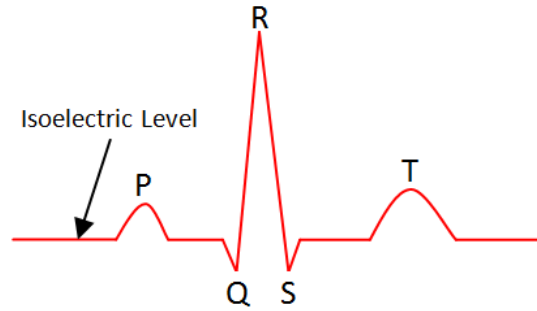
Figure 1. Normal ECG Morphology and Waves

Resting ECG machines with twelve leads, i.e. views of the heart, are used to monitor patients' ECGs. However, fewer leads can be used, as is the case for Holter monitors. These portable devices record the heart's activity for future offline diagnosis. They are useful for monitoring arrhythmias, whose presence is sporadic. Modern Holter monitors make use of two-to-twelve leads. For the case of other wearable ECG sensors, only one lead may be present. Therefore, one of the standard one-lead configurations must be used, referred to as the limb leads I-III.

2.2.2 Detecting heart attacks by electrocardiography

Approximately seventy percent of heart attacks are detectable in the ECG; the remaining thirty percent are not recognizable due to various reasons such as small infarctions, multiple infarctions, and electrocardiography is an indirect method [3]. Heart attack diagnosis relies on the analysis of the ST segment of the electrocardiogram. This research focuses on STEMIs and as such, the detection criteria presented in this section pertains only to STEMIs.

Clinically, to diagnose a heart attack the following criterion is applied: abnormal ST segment elevation (with respect to the isoelectric level) of greater than 0.1 mV in two or more contiguous limb leads [3-6]. Furthermore, the location of the heart attack can be determined by

examining different leads. For example, elevation in leads II, III and aVF indicates an inferior infarction, while elevation in two or more precordial leads indicates an anterior infarction.

Figure 2 displays ECG traces for normal and ST segment elevation. For the normal case, the ST segment is at approximately the same level as the isoelectric line. Therefore, the ST segment is not elevated according to the clinical diagnosis criterion. However, for the heart attack case, the ST segment elevation trace, the ST segments, highlighted in yellow, are clearly elevated with respect to the isoelectric level. The elevation is about 0.6 mV (the standard ECG scale is 1 mV per division).
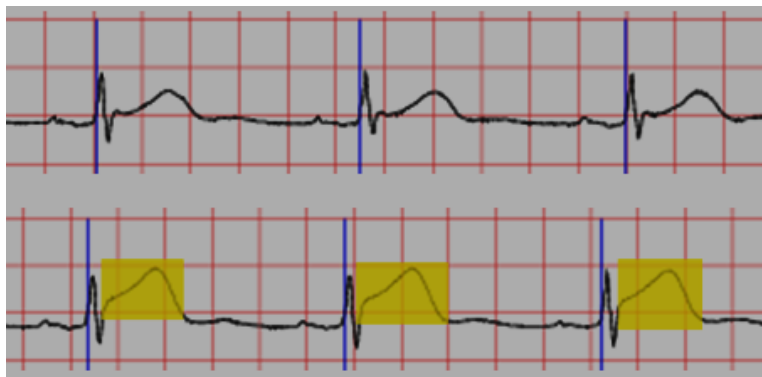
Figure 2. Top: Normal ECG • Bottom: ST Segment Elevation.

(ECG waveforms were plotted using the ATM tool from Physionet)

3.0   SMARTPHONES AS A PLATFORM FOR ECG PROCESSING

To develop a real-time, portable, accurate heart attack detection system for smartphones, first, the correct framework must be created. *HeartToGo* is the custom-developed graphical user interface (GUI) that is the backbone for ECG processing on a smartphone. This chapter will describe this platform [which the author created], which has been previously published in [7].

3.1   MOTIVATION

As previously stated, computationally powerful resting ECG machines lack the portability needed for continuous CVD monitoring. Three types of ECG solutions are possible: 1) those that store information to be diagnosed off-line after data collection is complete; 2) those that use remote connections to provide real-time diagnosis via a separate server; 3) those that perform real-time diagnosis within the device itself. Among the first type of systems, Holter monitors and event recorders stand out, such as GE's SEER (GE Healthcare, Waukesha, WI 53188), Philips's DigiTrack (Philips Healthcare, Andover, MA 01810), and Midmark's IQmark (Midmark Corporation, Versailles, OH 45380), among others. These devices only provide recording and monitoring capabilities and no real-time classification of ECGs because the classification is performed off-line. The second type utilizes telemedicine functionalities via a remote real-time monitoring system [8-10]. Most of them make use of mobile phones/PDAs to collect the ECG

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data and send them to a monitoring center where the analysis and classification is performed, thus depriving the user of real-time feedback. For the third type of systems, researchers have proposed some intermediate level of local real-time classification, such as the classification of heart beats, by using up-to-date smartphones or PDAs [11-14], but these do not provide a complete CVD diagnosis solution.

One contribution of this research is to provide a solution to bridging the gap between portable smartphone ECG monitors and resting ECG machines by providing the user with real-time ECG acquisition and display, beat classification, and the same statistical summaries available on resting ECG machines, which include: RR, P, and QRS durations; PR, QT, and QTc intervals; and average, high and low heart rates.

3.2   STATE-OF-THE-ART TEST BED

A state-of-the-art test bed for smartphone ECG processing was constructed on an HTC Ty TN II Windows Mobile 6 smartphone, as shown in Figure 3. The smartphone has a 400 MHz arm processor and 128 MB of ram. The phone processes ECG data provided by the Alive ECG sensor, also shown in Figure 3. The core components of the system are data acquisition, real-time ECG display, plug-in-based ECG processing, and cardiac summary reports, which are described in the following subsections.
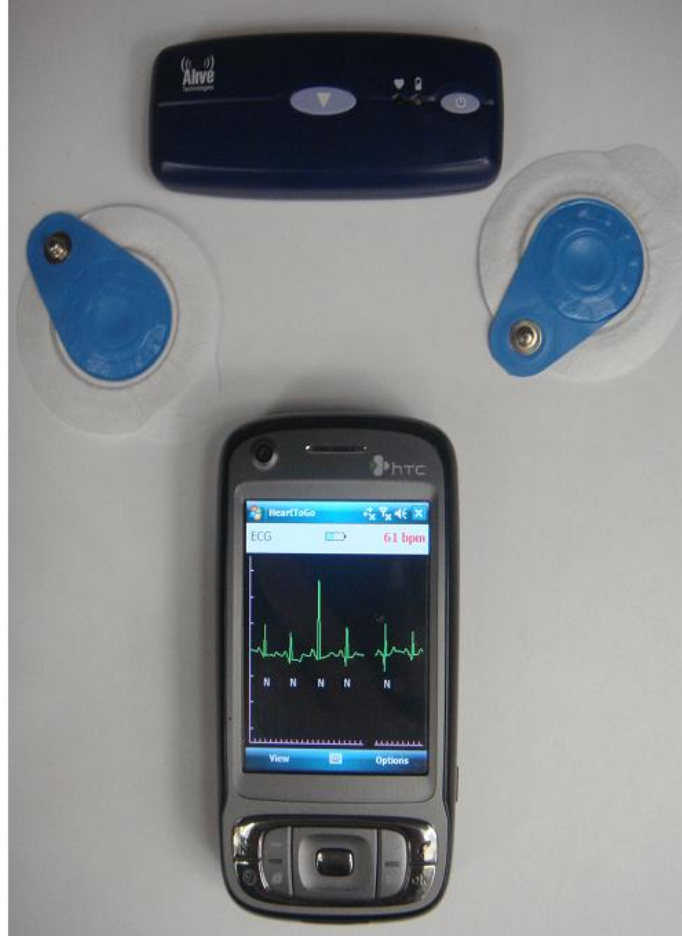
Figure 3. Smartphone ECG Processing Test Bed

Top: Alive ECG Sensor • Bottom: Windows Mobile 6 Smartphone

3.2.1 Data acquisition

To acquire real-time ECG signals, Alive Technology's (Alive Technologies Pty. Ltd., Robina, Queensland 4226, Australia) state-of-the-art wireless ECG heart monitor, which is a light-weight (60 g with battery), 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 was used. It is equipped with a class 1 Bluetooth transmitter, which can send its data to smartphones or other wireless devices. Also, the monitor is equipped with a 3-axis

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accelerometer. Furthermore, the ECG signal from the monitoring session can be recorded to a secure digital (SD) card that plugs into the sensor, allowing for optional offline analysis by a physician similar to that of a Holter monitor. Note that the recording length varies with the size of the SD card used (e.g. a 1 GB card could store 40 days worth of continuous ECG data).

HeartToGo, the multi-threaded C# application we developed for the real-time ECG display, processing, and cardiac summary reports, runs on Windows Mobile Smartphones. The Alive heart monitor communicates with *HeartToGo* using a Bluetooth serial port profile (SPP) connection. *HeartToGo* uses a dedicated thread to process the incoming Bluetooth data stream, which is made up of variable length packets containing both ECG data samples and acceleration data samples. Once the input data is read, parsed, and verified, thread delegates manage the sharing of the new ECG samples between the display and feature extraction threads in order to avoid cross-threading errors.

3.2.2   Real-time Display

As real-time ECG data arrives at the phone, the Bluetooth communication thread passes the data to the display thread for plotting on the screen. Different threads are used for display and data acquisition to obtain a responsive GUI and increase thread-level parallelism.

The ECG signal is plotted on the fly on the phone as data arrives at a sampling rate of 300 Hz, shown in Figure 4. Four different levels of magnification (1x, 2x, 4x, and 8x) were implemented to allow for a close-up examination of the ECG signal and are shown in Figure 4. The axis for the ECG plot conforms to the clinical standard of a resting ECG machine: the scale for the vertical voltage axis is 0.5 mV per tick, and the scale of the horizontal time axis is 200 ms per tick. Moreover, each beat is classified and an annotation is shown below each QRS complex;

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this is shown in Figure 4 with the "N" marking to signify a normal beat. If the beat had been a premature ventricular complex (PVC) beat then "V" would be displayed below the beat. Also, besides the real-time ECG signal, the average heart rate and battery life level of the heart monitor are displayed. Furthermore, if desired, the user can also switch between plotting the 3-axis acceleration trace instead of the ECG signal, as shown in Figure 5.
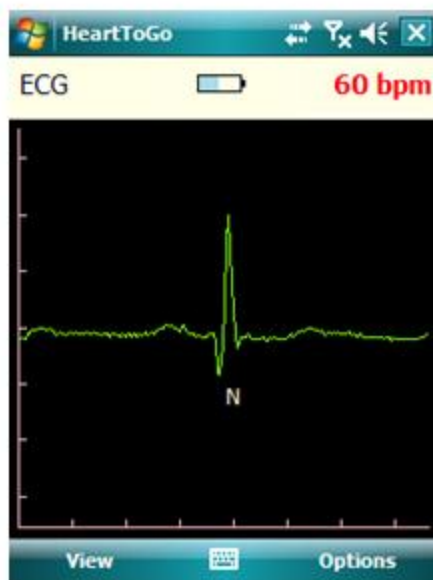
Figure 4. Real-time ECG Display at Different Magnifications

(a) 1x (b) 2x (c) 4x (d) 8x
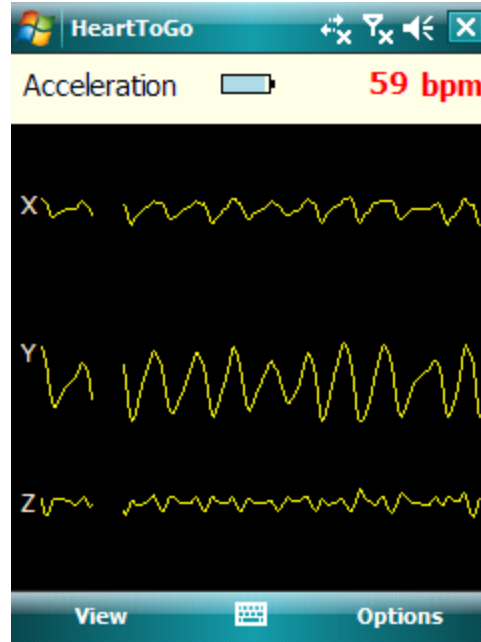
Figure 5. Real-time Three-axis (X, Y, and Z) Accelerometer Trace

3.2.3   Plug-in-based ECG processing

Feature extraction and classification is implemented on the smartphone as a separate dynamic linked library (dll) from the main *HeartToGo* application and runs on its own thread. There are two advantages to this approach. First, due to the computationally intensive math required, the plug-ins can be written in C++ to improve execution speed as opposed to C#. This language which was used for the GUI since it has a streamlined implementation in Windows Mobile using the .NET Framework, but runs slower than C++ code. Second, by using this approach, different dll plug-ins can be created for different CVDs without changing the main program, which is responsible for data acquisition and display. This makes the process of detecting different cardiac conditions, e.g. PVC beats vs. heart attacks, much easier from the perspective of the programmer writing the algorithms. Furthermore, it simplifies debugging and validating the algorithm code since it is a library and therefore platform independent and separate from the GUI.

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3.2.4 Cardiac Summary Reports

The same statistical cardiac summary reports provided by standard resting ECG machines are implemented in *HeartToGo*. Both cardiac statistics and features are extracted from the ECG signal in real time. Figure 6 (a) presents the cardiac features report, which includes the RR duration, P duration, QRS duration, PR interval, QT interval, and QTc interval. Figure 6 (b) shows the cardiac statistics, consisting of the average, high, and low heart rate and the total number of beats, as well as the number of normal and PVC beats. Also, the number of ST episodes (the warning sign for a heart attack) is shown in the cardiac statistics. Furthermore, a multilevel warning system is triggered when ST episodes occur so that the user does not have to continuously monitor the cardiac summary reports; this is described in-depth in chapter V.
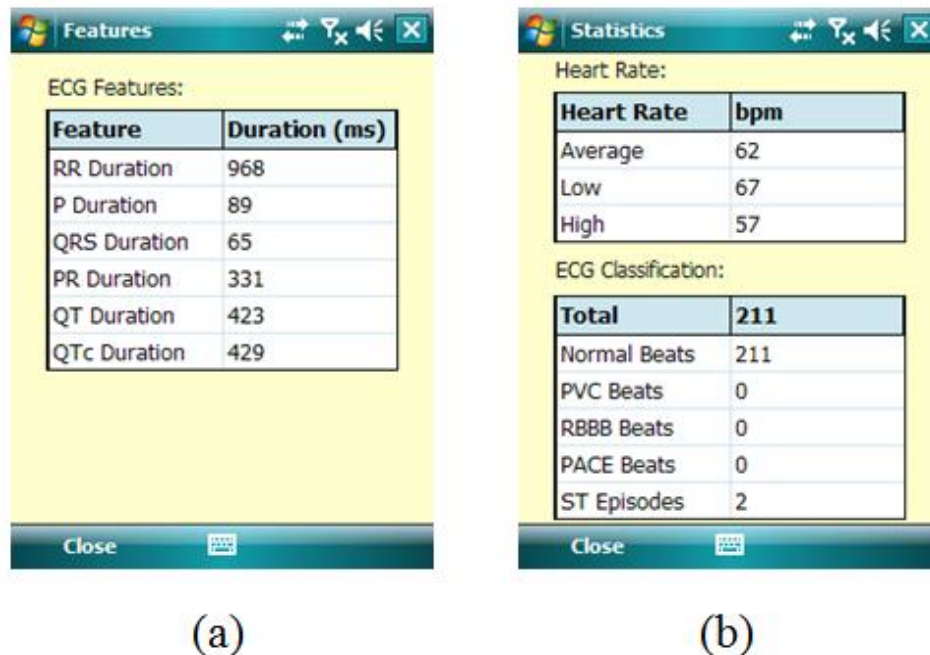
Figure 6. Cardiac Summary Reports: (a) Features (b) Statistics

4.0 ACCURATE, REAL-TIME, CONTEXT AWARE HEART ATTACK DETECTION ALGORITHM

The most important component of heart attack detection on a smartphone is choosing the correct algorithm to detect heart attacks. This chapter will propose an accurate, real-time, context aware heart attack detection algorithm for use on the target smartphone platform.

4.1 MOTIVATION

STEMIs start to occur when there is an abnormal ST segment. When viewing the ECG on the monitor of a resting ECG machine, a physician can easily determine the ST segment location and its level. Furthermore, resting ECG machines can automatically classify ST segments by comparing the ST level at a predefined distance from the R-peak to the isoelectric level [15]. However, this segment is not easily recognized by a computer due to the complex morphology (small magnitude waves that are easily obscured by larger, sharper waves) of the body's ECG signal. Many algorithms exist for offline ST segment analysis. The most popular methods are wavelet [16], rule-based [17], artificial neural networks [18], time domain-based methods [19], use of a predetermined location of the ST segment by a cardiologist [20], and reference sets from an ST database [21]. While wavelets and neural networks are powerful solutions for offline analysis, they are not suitable for a smartphone based solution because they are extremely

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computationally intensive. The formula based and cardiologist based methods for determining the ST segment are very computationally inexpensive, but only measure the ST segment's level at a predefined distance from the R-peak and do not consider the morphology of the segment.

Therefore, there exists a need for an algorithm capable of providing both reliable beat classification and being lightweight and accurate enough to run on a smartphone based platform. Clinically, ST elevation occurs when the ST segment is elevated greater than 0.1 mV [3-6]. This linear decision leads to a hypothesis of linear classification. Therefore, the support vector machine (SVM) will be proposed and evaluated as a heart attack classifier in this research. Furthermore, a portable smartphone platform allows the users to move freely. In a clinical setting, the patient would be confined to a bed and muscle and motion artifacts would not be a problem. However, with the wearable ECG sensor the algorithm would need to be aware of these artifacts since ST segment elevation detection is very sensitive to noise [22]. Moreover, these artifacts are very difficult to remove from the signal by standard methods such as filtering because their frequency components are in the same range as the ECG's frequency spectrum [23].

4.2   RELATED WORK

As with most ECG topics, computer-detectable ST segment elevation has been previously studied. This section will survey existing algorithms which make use of wavelet, rule-based, artificial neural networks, time domain-based methods, use of a predetermined location of the ST segment by a cardiologist, and reference sets from an ST database.

In [16] X. Li, *et al.* present ST-T complex automatic analysis using the wavelet transform. Their work focused on locating the fiducial points S, J (the start of the ST segment), and T. The wavelet transform was used at different scales to detect the different fiducial points. Although the ST fiducial points were identified in this work, the ST segments were not classified as normal or elevated.

In [17] C. Papaloukas, *et al.* apply a rule-based method to ST segment classification. First, they locate the QRS complex and identify fiducial points based on empirical formulas. Next a rule-based method is applied to classify the ST segments. The rules are based on the value of the ST segment after a predefined time from the R peak and the slope of the segment. The European ST database was used for testing.

In [18] T. Stamkopoulos, *et al.* detect ischemia using nonlinear PCA neural networks. The ST segment is classified into two groups: normal and abnormal. Abnormal groups are actually comprised of artifacts, ST elevations, and ST depressions. The radial basis function neural network is used and the algorithm is tested using the European ST database. A classification accuracy of 80% for normal beats and 90% for ischemic beats is reported.

F. Badilini, *et al.* detect ischemia from Holter monitor recordings in [19]. Empirical formulas are provided to create a window for locating the ST segment based on heart rate, i.e. the RR interval. Next, the resulting windowed ST segment is classified.

D. Fischell, *et al.* patent a system for the detection of cardiac events in [20]. Their system requires that a physician assess the location of the patient's ST segment with respect to the QRS complex. Based on this fixed location, an algorithm then monitors the ST segment for changes in elevation. Should a change in elevation occur a warning system is triggered.

In [21] G. Jeong and K. Yu use reference sets to classify ST segments. A polynomial approximation of the ST segment is used. First, QRS detection is performed, followed by the polynomial approximation to classify the ST shape. ST type is determined by comparing with the slope of the reference ST type. ST type by comparing The European ST database is used for testing data.

4.3   PROPOSED HEART ATTACK DETECTION ALGORITHM

A real-time, accurate, context aware ST segment classification algorithm using PCA for feature extraction and an SVM for normal or abnormal (heart attack) classification is proposed for heart attack detection. The detection workflow is shown in Figure 7. First, real-time ECG data is segmented beat-by-beat using a QRS detector. Next, ST segments are extracted from the individual heartbeats and then downsampled to eliminate redundancy and speed computation time. PCA is further used for dimensionality reduction and provides two principal components for the classifier. An SVM is used to classify the ST segments into two categories: normal or ST elevated. Finally, a filtering operation is performed to detect ST episodes, which are clinically significant signs of heart attack [24].

First, the algorithm was prototyped in MATLAB due to its ease in implementing algorithms and predefined functions, including PCA and SVM. Next, the code was translated to C for use with the smartphone application *HeartToGo*. The algorithms were validated throughout each stage of the design, but the most extensive testing will be discussed in chapter VI. The following subsections will provide a greater explanation of the individual components to the heart attack detection algorithm.
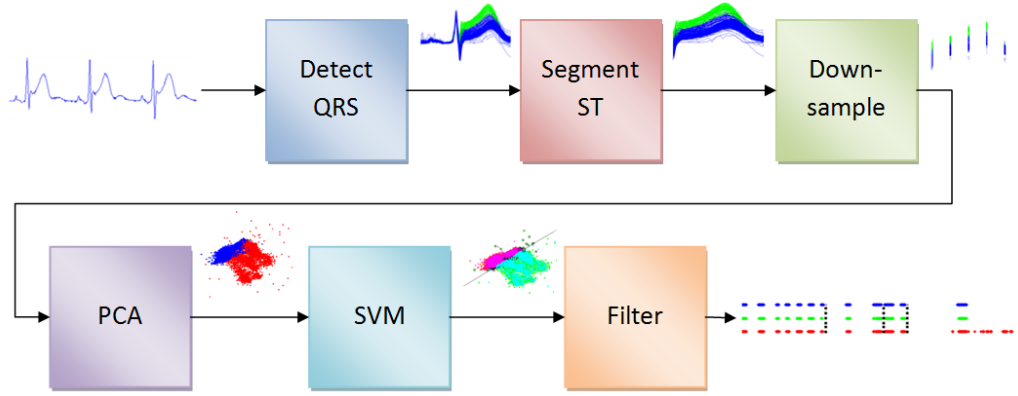
Figure 7. ST Episode Detection Workflow

4.3.1 Test data

The European ST annotated database [24] from Physionet [25] will serve as a gold standard for test data, as it is expertly annotated by cardiologists for use in ST segment research, testing and validation. The sampling rate of the data is 250 Hz with a 12-bit resolution over a 20 mV range. Four records (numbers 105, 118, 119, and 121), each from different patients, were selected as test data. The selection criteria are the following:

- Must contain ST elevation episodes

- Cannot contain excessive noise or motion artifacts

- Must be from a lead that is able to be monitored using a single lead ECG sensor, i.e. a limb lead

- Must all be from the same lead so morphology differences across leads will not be introduced

The first ten seconds from each of the selected records are shown in Figure 8. Note the morphology differences between patients. For example, record 119 shows inverted T waves.

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Also, the data were recorded using limb lead III. This lead was chosen because 1) no limb lead II data were available and 2) limb lead I data did not meet any of the criteria above.

With this data set, 21,568 heartbeats are available, roughly $1/4^{th}$ of which are ST segment elevated. Furthermore, 12 cases of ST episodes are observed in the test data, which will serve as the heart attack warning. These episodes consist of at least thirty seconds of ST elevated beats in order to be clinically relevant [24]. Table 1 provides a breakdown of the number of normal beats, number of ST elevated beats, and the number of ST episodes for each record.

(a) 105
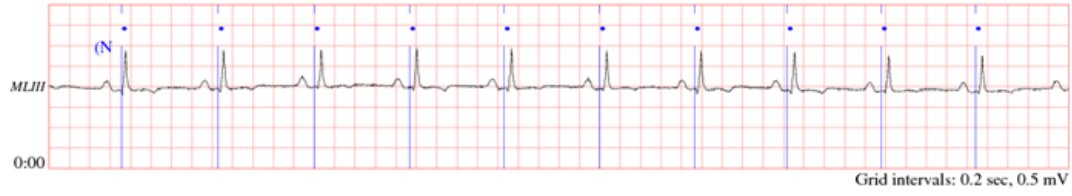
(b) 118
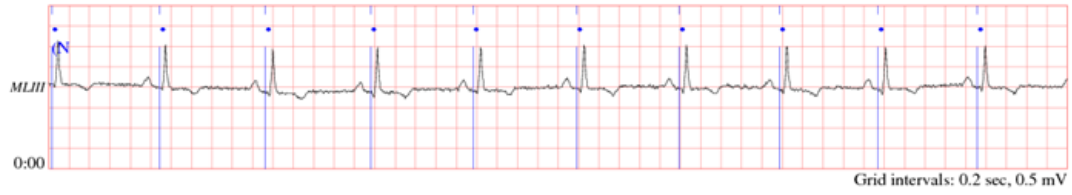
(c) 119

(d) 121

Figure 8. Ten Second Clips of Selected Records of Test Data

Records (a) 105 (b) 118 (c) 119 (d) 121 from the European ST Database [24]

(ECG waveforms were plotted using the ATM tool from [25])

Table 1. Breakdown of test data beat classification

Record	105	118	119	121	Total
Normal Beats	4411	3472	776	8152	16811
Elevated ST Beats	2170	902	999	686	4757
ST Episodes	7	2	2	1	12

4.3.2 Heartbeat detection and segmentation

Heartbeat detection is an extremely important stage in the overall heart attack detection algorithm. Without a properly functioning beat detector, ST segments would not be able to be located. Since this research focuses on detecting ST segment episodes, and since beat detection is a very well solved problem, beat detection will be performed by the classic Pans-Tompkins beat detector [26-28], which has a sensitivity of 99.69% and positive prediction of 99.77% when evaluated with the MIT-BIH arrhythmia database from Physionet [25].

After performing on-the-fly beat detection, the heartbeats are segmented, as shown in Figure 9. To ensure that the entire beat is captured, a window length of 201 is used, which corresponds to 0.8 seconds. Figure 9 clearly shows the difference between normal beats, and ST elevated beats. As the ST segment continues to rise above the isoelectric level the beat remains normal, but when the level crosses the 0.1 mV threshold the beat is then classified as ST elevated. Note that in the Figure 9 the two classes: normal and ST elevated came from the expert annotations of the European ST database.
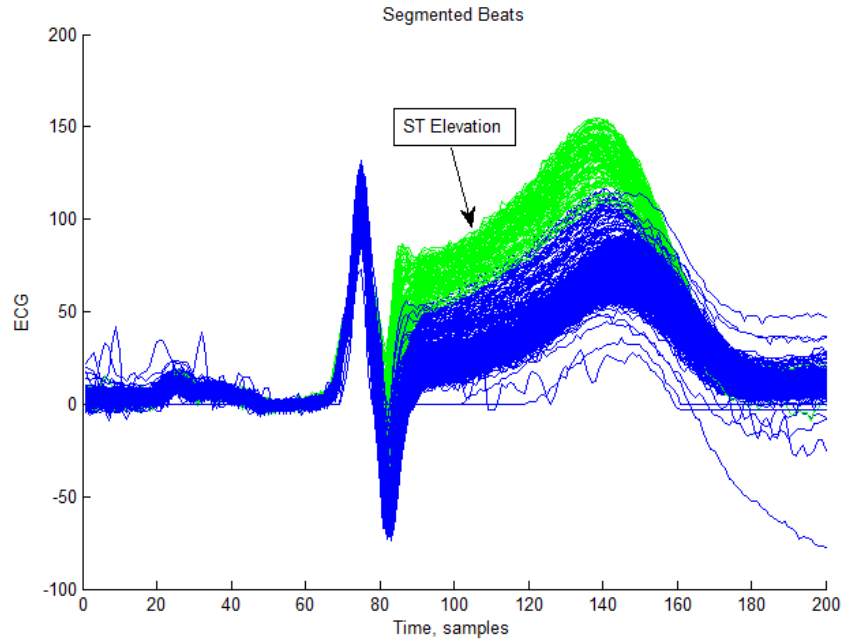
Figure 9. Segmented Beats

Blue: Normal • Green: ST Elevation

Following beat segmentation, the next stage of the QRS detection algorithm is re-segmenting the beats into individual ST segments. Again, this is performed using a window. The length of the window was chosen to be 30, which corresponds to 120 ms, which ensures that the entire ST segment is captured for processing. Figure 10 shows the segmented ST waves. Again, the segments are classified as normal or ST elevated using the expert annotations from the European ST database. Examining the segments, it is observed that maximum separation occurs in the middle portion of the wave. At the beginning of the segments there is noticeable separation, but it is very minimal, and at the end of the T wave the two classes blend back together.
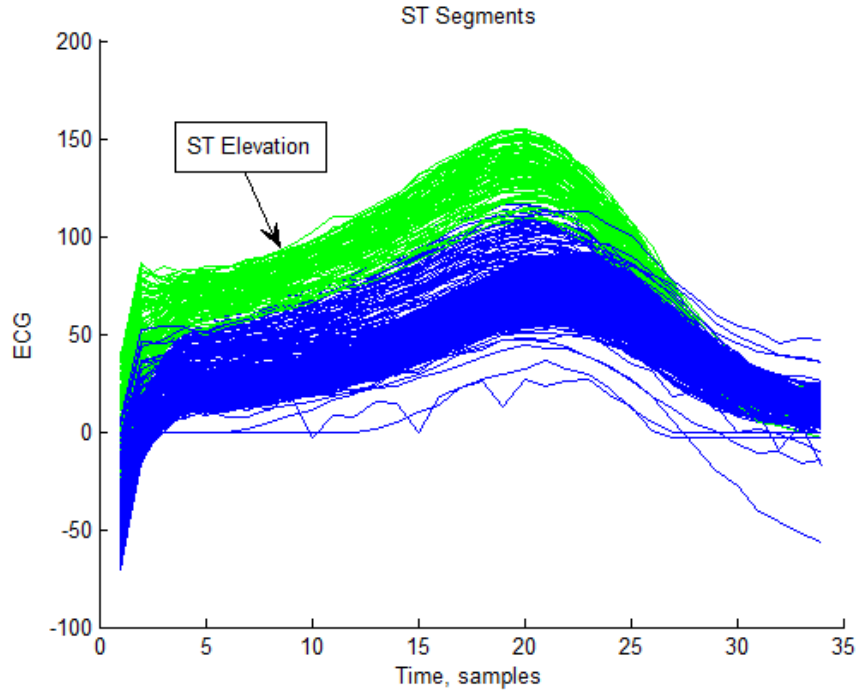
Figure 10. Segmented ST Segments

Blue: Normal • Green: ST Elevation

4.3.3 Dimensionality reduction

4.3.3.1 Background

Dimensionality reduction reduces extra redundancy and makes classification easier. For a smartphone platform with limited RAM and processing power, compared to a PC, it is especially important because it reduces the classification execution time and data size in memory. Data reduction will be accomplished first by downsampling, which will remove redundant data points, and second by applying PCA to reduce the dimensionality down to two principal components for clustering.

First, downsampling was skipped to determine the classification accuracy just using PCA. Component analysis is used to determine the correct features for classification. PCA

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projects n-dimensional data onto a lower-dimensional subspace (two dimensions in this case), while maintaining an optimal sum-squared error [29]. As given in [29], first, the squared-error criterion is defined by the following:

$$J_0(\mathbf{x}_0) = \sum_{k=1}^{n}\|\mathbf{x}_0 - \mathbf{x}_k\|^2 \tag{1}$$

where the samples $\mathbf{x}_1$, …, $\mathbf{x}_n$ are represented by a single vector $\mathbf{x}_0$, and the sum of the squared distances between $\mathbf{x}_0$ and $\mathbf{x}_k$ are as small as possible. The solution is to let $\mathbf{x}_0$ equal the sample mean, $\mathbf{m}$. Since the mean is a zero-dimensional representation of the data which doesn't show any variability, consider a one dimensional projection:

$$\mathbf{x} = \mathbf{m} + a\mathbf{e} \tag{2}$$

where $\mathbf{e}$ is a unit vector in the direction of the line and the scalar a corresponds to the distance of any point $\mathbf{x}$ from $\mathbf{m}$. Solving for ak yields:

$$a_k = \mathbf{e}^t(\mathbf{x}_k - \mathbf{m}) \tag{3}$$

Next, the best direction of $\mathbf{e}$ needs to be found, which is performed using the scatter matrix, $\mathbf{S}$, given by:

$$\mathbf{S} = \sum_{k=1}^{n}(\mathbf{x}_k - \mathbf{m})(\mathbf{x}_k - \mathbf{m})^t \tag{4}$$

The largest eigenvectors are then selected, which correspond to the largest eigenvalues of the scatter matrix to find the best projection:

$$\mathbf{S}\mathbf{e} = \lambda\mathbf{e} \tag{5}$$

Finally, projection to a lower-dimensional space d_n is given by:

$$\mathbf{x} = \mathbf{m} + \sum_{i=1}^{d_n} a_i\mathbf{e}_i \tag{6}$$

4.3.3.2 Results

MATLAB was used to perform PCA on the ST segment test data. The PCA of the ST segments is shown in Figure 11. There are two clusters: normal and ST elevated, with slight overlap between the two clusters. After implementing PCA, initial SVM classification was performed to assess the opportunity for downsampling prior to PCA in order to reduce the size of the data array during PCA. Figure 12 presents the trade-off between accuracy and execution time for downsampling. As shown, classification accuracy is approximately constant at 96% during the range of sampling rates from 40 – 250 Hz. Below 40 Hz classification accuracy begins to drop. Below 8 Hz classification accuracy drops drastically. On the other hand, execution time increases linearly as sampling frequency increases. Taking advantage of the constant classification accuracy in the 40-250 Hz region, 50 Hz is selected as the new downsampling rate, which is $1/5^{th}$ the original sampling rate of 250 Hz, yet the accuracy remains at 96%. Execution time decreases from 3.2 µs to 0.5 µs, achieving an 84% speedup, which is especially important for a smartphone platform that has to meet real-time deadlines.
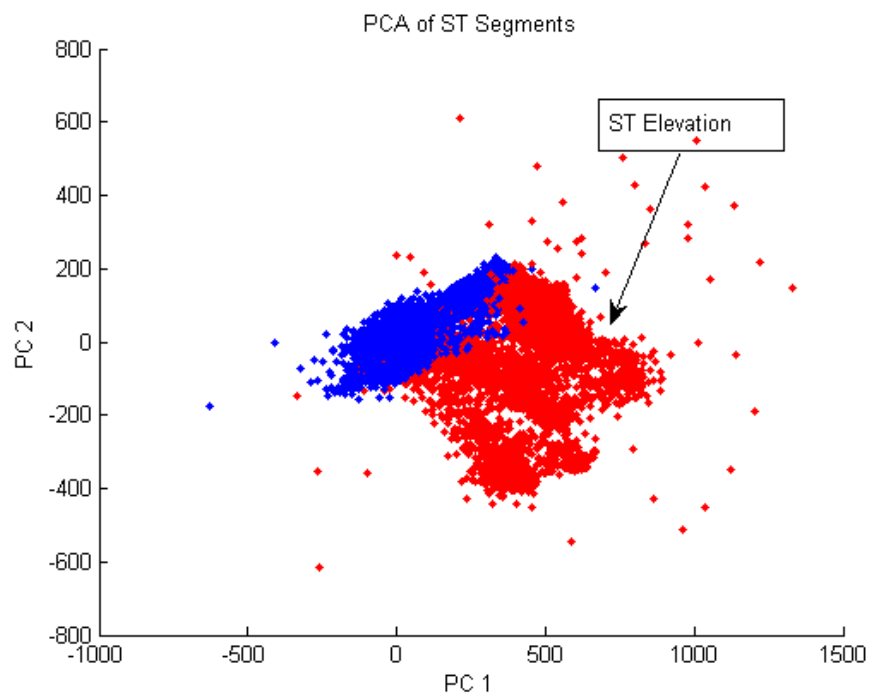
Figure 11. PCA of ST Segments

Blue: Normal • Red: ST Elevation
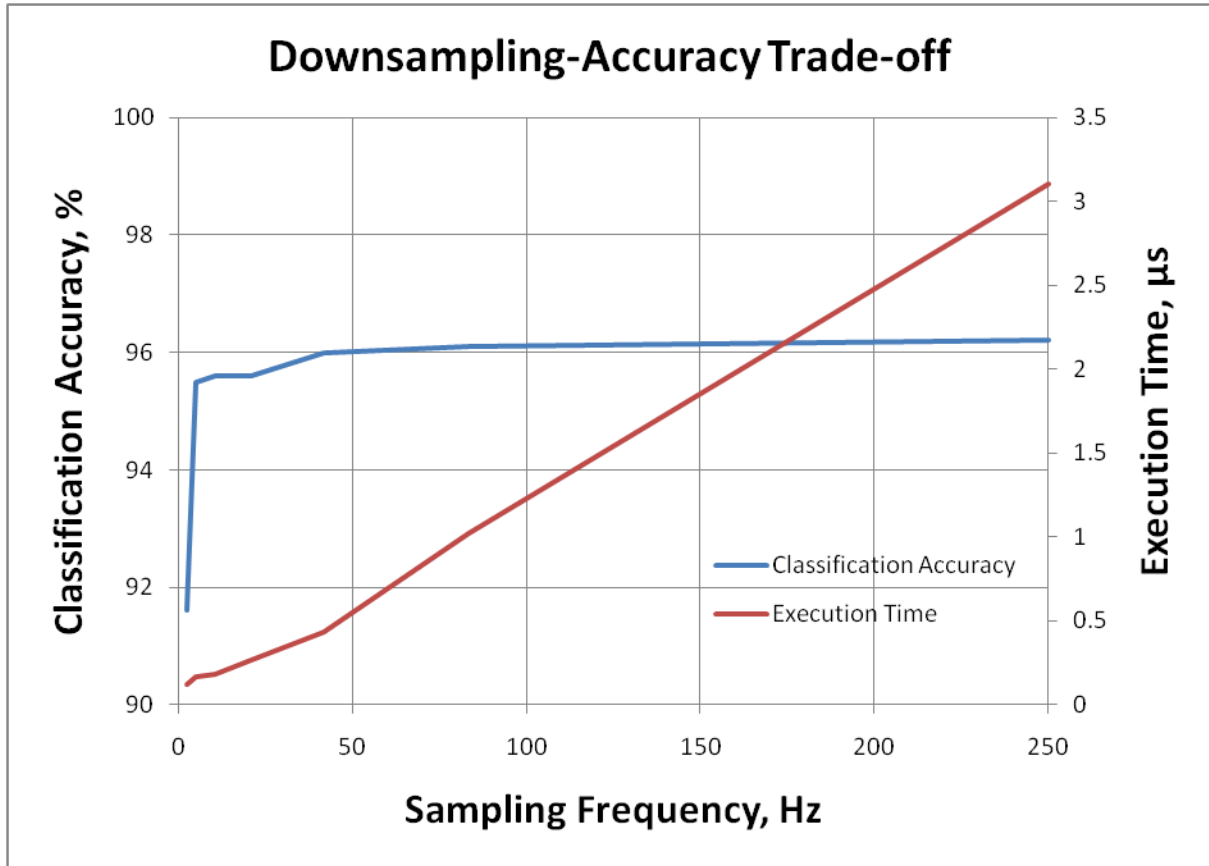
Figure 12. Downsampling: Accuracy vs. Execution Time Trade-off

4.3.4 Classification

4.3.4.1 Background

Classification of beats into normal and ST elevated groups requires defining a boundary between the two regions. This research uses a support vector machine (SVM) to construct the boundary between classes. For a smartphone with limited computing power, compared to a PC, the most light-weight on-the-fly classification method is desired, which would be a linear classifier. With a linear clinical criterion for ST segment elevation occurring at levels greater than 0.1 mV [3-6], it is hopeful that a linear SVM can also be used.

SVMs are classifiers that rely on preprocessing the data to higher dimensions than the original feature space. With an appropriate nonlinear mapping kernel, φ, two-class data can be separated by a hyperplane [29]. For n patterns ($k = 1,\ldots n$) $\mathbf{x}_k$, which have been transformed to $\mathbf{y}_k = \varphi\ (\mathbf{x}_k)$, let $z_k = \pm\ 1$depending on whether the pattern is in class C1 or C2. From [29], a linear discriminator in the augmented space is:

$$g(\mathbf{y}) = \mathbf{a}^t\mathbf{y} \tag{7}$$

A separating hyperplane ensures that:

$$z_k g(\mathbf{y}_k) \geq 1, k = 1, \ldots n \tag{8}$$

where the support vectors are those where $z_k g(\mathbf{y}_k) = 1$. These support vectors are equally close to the hyperplane (note that Figure 13 circles support vectors) and are the training samples that define optimal separating hyperplane. Accordingly, they are also the most difficult patterns to classify [29].

This section examines the classification results using different kernels: linear, quadratic, multilayer perceptron (MLP), and radial basis function (RBF) to determine which is the most suitable for use in the heart attack detection algorithm.

4.3.4.2 Results

MATLAB is used for algorithm training and verification due to its prewritten classification toolboxes. To perform the training and testing cross-validation is used. Twenty-five percent of the normal heartbeats (4,200) and twenty-five percent of the ST elevated beats (1,200) from the expertly annotated training set are randomly selected for use in the training stage and the remaining seventy-five percent of beats are then classified with the trained SVM. Classification training results are shown in Figure 13 for each kernel and the classification accuracy is outlined

in Table 2. The linear, quadratic, and RBF kernels have an accuracy of 96%. The MLP clearly is a poor fit of the data, as shown in Figure 13, and its classification accuracy is 86%.

The linear classifier is chosen as the best option because it is the most computationally inexpensive and maintains high classification accuracy. Note that the quadratic and Gaussian RBF ($\sigma = 1$) kernels also have classification accuracies of 96%, but they are over-fitting the data, which is evident by encircling the normal data. It is expected that if the quadratic kernel contained a linear component then higher accuracy would be obtained, and the normal data would not be encircled.

Further evaluation of the linear SVM classifier is shown in Table 3. The classification accuracy for each data set is independently evaluated. Accuracy ranges from 95% to 99%, with a weighted average of 96%. Note that a weighted average was used because the different datasets are different lengths, as shown in Table 1. Furthermore, the linear SVM classifier presented in this thesis with classification accuracy of 96% is compared to other existing classifiers in Table 4, whose accuracies range from 70% - 91%. One reason the linear classifier presented in this work has a higher accuracy is because it is specifically designed for solving the two class problem of normal and ST elevation. Other classifiers presented do not focus on STEMI detection, but instead on general ischemia detection, so while they are more robust, e.g. able to detect ST depression, they are not as accurate at focusing on ST elevation.
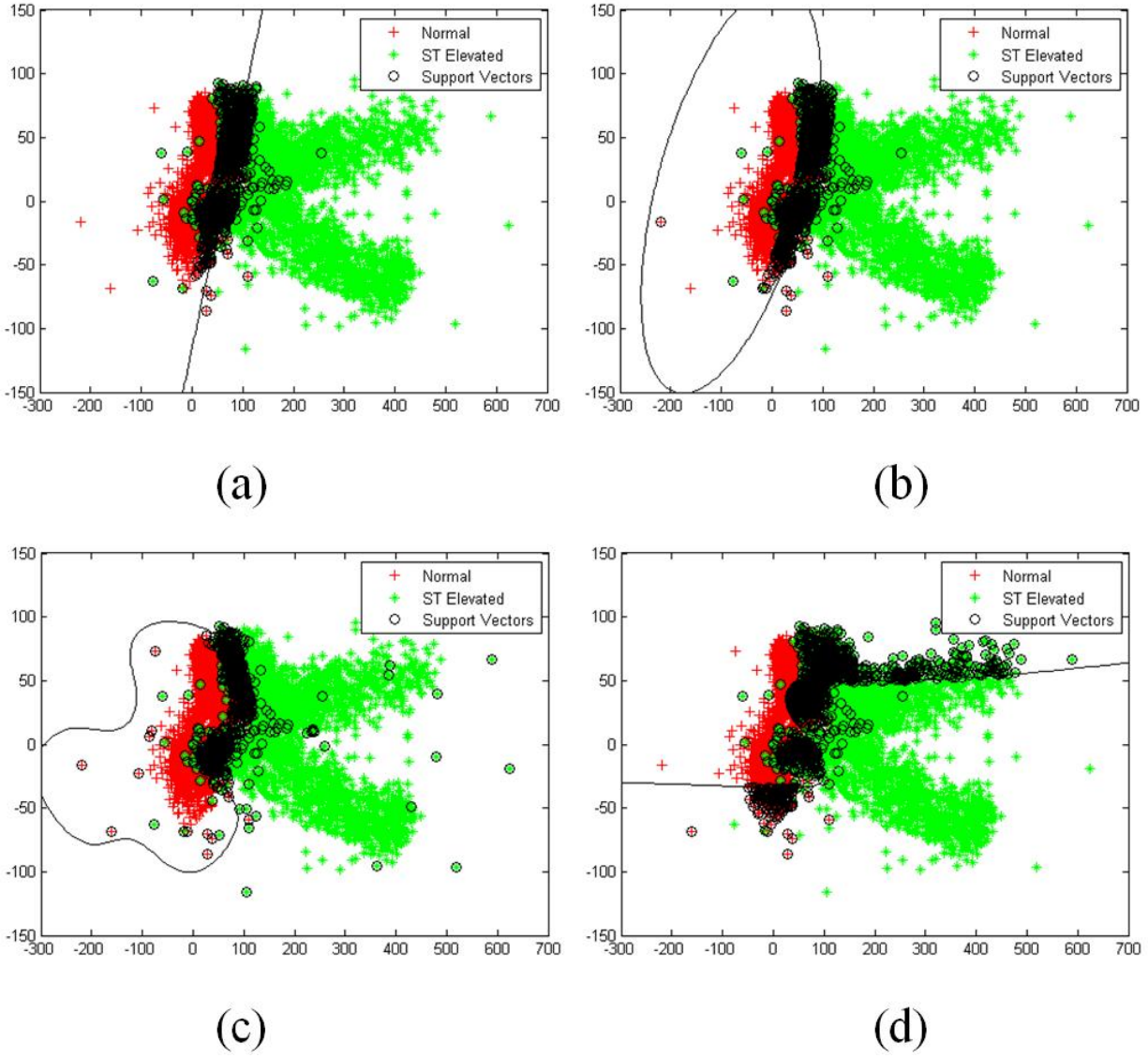
Figure 13. SVM Classification of ST Segment with Different Kernels

(a) Linear (b) Quadratic (c) RBF (d) MLP

Table 2. ST Segment SVM Classification Accuracy with Different Kernels

SVM Kernel	Classification Accuracy (%)	Overfit?	# of Support Vectors
Linear	96.2	No	1651
Quadratic	96.2	Yes	1631
RBF	96.1	Yes	1364
MLP	85.9	Yes	2171

Table 3. SVM Classification Accuracy of Test Data

Record	105	118	119	121	Weighted Average
Classification Accuracy (%)	95.9	99.3	96.2	98.2	96.2

Table 4. SVM Classification Accuracy vs. Other Methods

Method	Accuracy (%)
PCA & SVM (This work)	**96**
Genetic Algorithm [30]	91
PCA & ANN [31]	79
HMM [32]	86
KL & Mahalanobis [33]	87
ANN Back propagation [34]	89
Rule-based [17]	70

4.3.5 Smoothing filter

After individual heartbeat classification, heart attack detection can be performed. As previously mentioned, one heartbeat with an elevated ST segment does not indicate heart attack. Instead, at least a thirty second episode of elevated ST segments is clinically significant [24]. To obtain the ST episodes a smoothing filter is used. This is necessary because 1) the heart attack detection algorithm is not 100% accurate and may misclassify a few beats in an ST segment and 2) ST episodes with duration of less than thirty seconds can be filtered out.

The proposed filtering algorithm is shown in Figure 14. First, individual heartbeats are classified as ST elevated or normal by the SVM classifier. If the beat is normal then no further action is required. On the other hand, if the beat is ST elevated, the next thirty seconds of beats

are summed (1 ≡ ST elevated beat, 0 ≡ normal beat). If the sum is greater than a certain threshold, i.e. there were a significant number of ST elevated beats in the episode, then it is classified as an ST episode and the warning system presented in the next chapter will launch. If the sum is less than the threshold the beat is reclassified as normal to prevent false alarms.
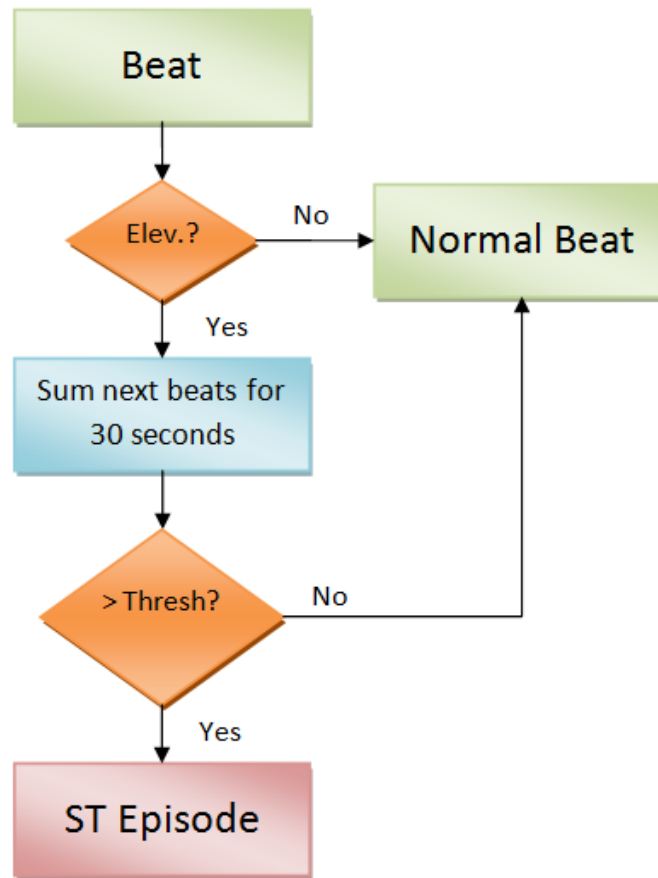
Figure 14. ST Episode Filter Algorithm

Filtering was performed on the classified results to verify the algorithm and compare the accuracy of filtering versus using the results directly from the classifier. Figure 15 plots the ST episodes in time. Expert annotated ST episodes from the database are used as a reference. As shown, the filtered results match the annotations: all ST episodes were detected and there were zero false positives. However, while the unfiltered ST episodes also detect all ST episodes, there

were cases of false positives, predominantly five, in test record 121. The beat-to-beat accuracy of filtering versus the unfiltered results as compared to the annotated data is shown in Table 5. From the tests performed, an 11% increase in accuracy results in beat-to-beat classification, mainly contributed to eliminating false positive beats.
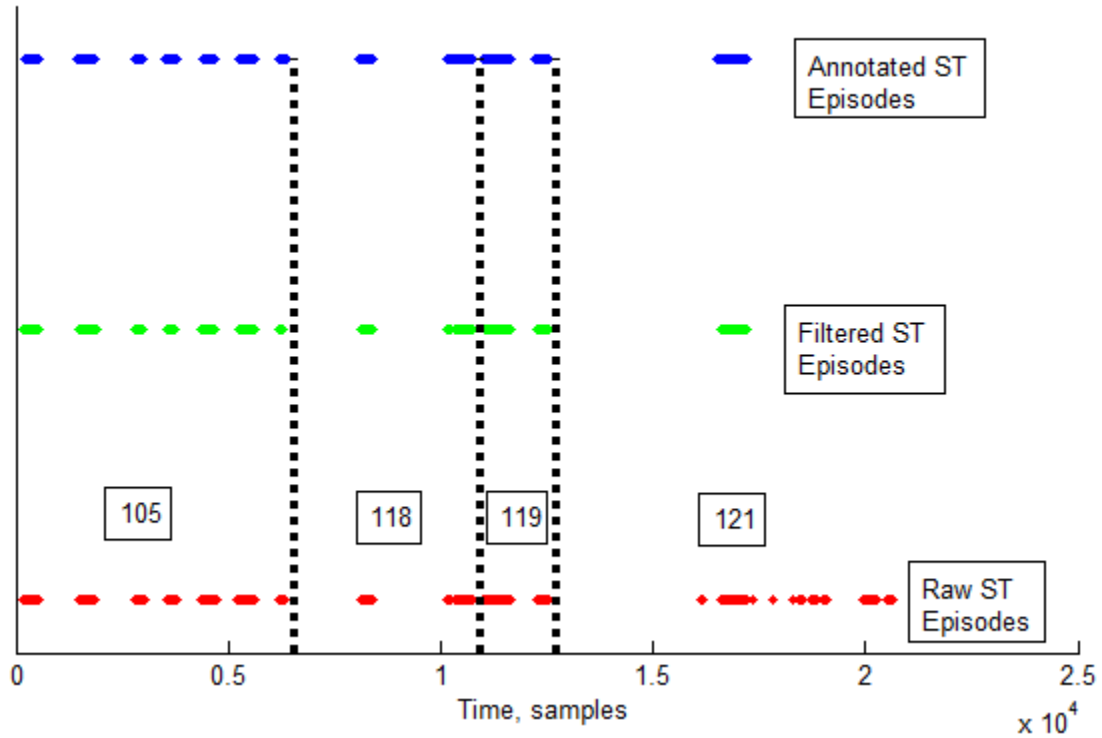

Figure 15. Comparison of Annotated and Calculated ST Episodes

Table 5. ST Episode Accuracy: Raw vs. Filtered

Record	105	118	119	121	Weighted Average
Unfiltered ST Episode Accuracy (%)	1.5	0.64	0.93	0.94	1.05
Filtered ST Episode Accuracy (%)	1.5	0.59	0.65	0.74	0.93

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4.3.6 Discussion

An accurate, real-time heart attack detection algorithm has been proposed, implemented, and tested. A classification accuracy of 96% was achieved, all ST episodes were detected, and zero false positives were reported when validating with the European ST database [24]. However, one disadvantage to the popular European ST database is that only ST episodes are expertly annotated. Individual beats on the other hand, are not annotated as to whether they are ST elevated or normal. Because of this, there are, in fact, ST elevated beats that are annotated as normal beats. While there are not many of these beats, this problem was evident in Figure 15, which shows that for the raw ST episodes there were short bursts of ST elevation which did not show up in the annotated episodes because their length was less than thirty seconds. Therefore, it is desired that for future testing a new database be created and that not only ST episodes are expertly annotated, but also the ST segment elevation level for each beat be provided for a more robust training and validation data set.

The heart attack detection algorithm presented consists of multiple stages: beat detection, ST segmentation, downsampling, PCA, SVM classification, and filtering. With the advent of multi-core processors for desktop computing, it is only a matter of time before they make their way into the smartphone market. This pipelined heart attack detection algorithm lends itself to parallelizations that could be exploited on a multi-core processor. In future work, this algorithm should be parallelized, which will have the advantage of running faster and therefore, ensuring that real-time deadlines are met. Furthermore, with a parallel workload the processing of extra leads of ECG data could be incorporated, once wearable ECG sensor technology advances to monitoring multiple leads.

4.4   INCORPORATION OF CONTEXT AWARENESS

Context awareness provides physical/environmental information to a computer. In this case, the context is body movement, i.e. acceleration data, which is provided by the Alive sensor's built-in accelerometer. This section will describe the usefulness of incorporating accelerometer data into ECG processing as well as provide testing results.

4.4.1   Motivation

Motion and muscle artifacts are a well-known problem in ECG processing. These artifacts are notorious for being very difficult to remove from the signal by standard methods such as filtering because their frequency components are in the same range as the ECG's frequency spectrum [23]. In a clinical setting, the patient would be confined to a bed and muscle and motion artifacts would not be a problem. However, a portable smartphone platform allows users to move freely, thus introducing muscle and motion noise. The wearable ECG sensor the algorithm needs to be aware of these artifacts since ST segment elevation detection is very sensitive to noise [22]. One way to detect excessive motion artifacts is to monitor the user's acceleration. By monitoring the user's acceleration for excessive movement, which significantly degrades the ECG signal, false alarms can be limited.

4.4.2   Implementation and testing

To introduce body movement context awareness into the heart attack detection algorithm, the acceleration data is first collected from the Alive ECG sensor's three-axis accelerometer (X, Y,

and Z corresponding to roll, pitch, and yaw axes, respectively). These data are then available to the heart attack detection algorithm for context consideration.

The proposed context awareness algorithm is shown in Figure 16. Each beat is first classified as normal or ST elevated. Normal beats require no context awareness processing because they will not trigger false alarms. However, if the beat is ST elevated the vector sum of the acceleration, i.e. sqrt($X^2+Y^2+Z^2$), is compared to a threshold. If the acceleration is less than the threshold, the beat remains classified as ST elevated. However, if the acceleration is greater than the threshold, the beat is reclassified as normal to prevent false alarms.

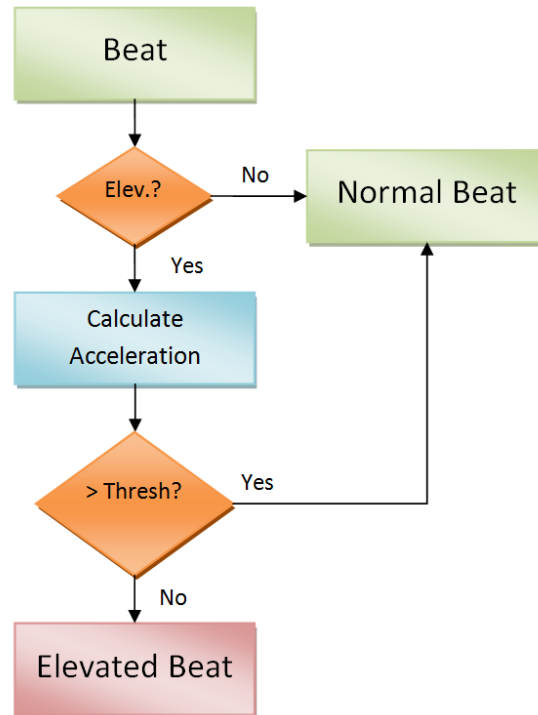**Figure 16.** Context Awareness Algorithm

Testing was performed to determine a reasonable threshold acceleration value. The Alive ECG sensor was worn while performing normal activities, and the maximum acceleration was recorded. To obtain a threshold, the ECG was viewed and the ST segment was scrutinized. If the ST segment contained artifacts pushing its value to greater than 0.1 mV above the isoelectric

level, the acceleration was too high. Experimental results show that an acceleration of 1 g will not introduce enough motion artifacts to cause false ST segment elevations. The accelerations during normal activities are shown in Figure 17, along with the threshold. As shown, jogging, climbing stairs, and tennis all contain maximum accelerations which exceed the threshold.
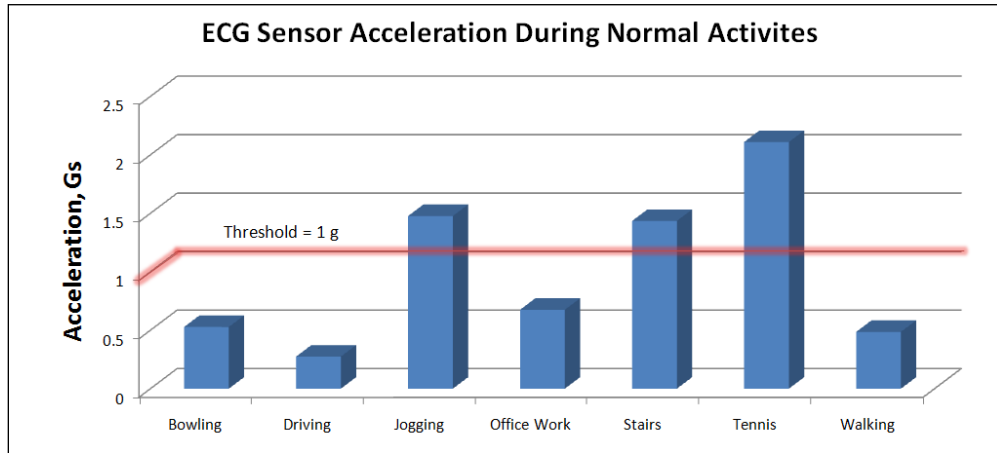

Figure 17. ECG Sensor Acceleration during Normal Activities

4.4.3 Discussion

Context awareness for ECG processing has only been briefly experimented with in this thesis and is a topic that deserves its own dedicated thesis for full understanding. The context awareness algorithm presented is not meant to be the most accurate and precise method of handling motion artifacts. Further experimentation should be performed in an in-depth study. Possible items to include are whether or not to use the magnitude of the acceleration, or if different components of acceleration cause more motion artifacts than others.

Also, note that the results presented in the previous section show that the maximum acceleration during jogging, tennis, and climbing stairs all exceed the acceleration threshold. This does not mean that the heart attack detection algorithm cannot detect a heart attack while

the user is engaging in these activities. Instead, it means that individual heartbeats are discarded only when the body acceleration at that instant in time when the beat occurred is so large that the ECG is no longer accurate.

5.0 MULTILAYERED REAL-TIME ALERT AND TELEMEDICINE SYSTEM

Resting ECG machines provide the most powerful ECG processing and provide real-time alerts and cardiac summary reports; however, these machines are not portable. On the other hand, portable Holter monitors only record the ECG signal and lack any real-time feedback. As previously mentioned, existing intermediate solutions exist that use smartphones to record the ECG signal and transmit the data via a telemedicine service to more powerful computers for processing [8-10]. While this is a step above the Holter monitors, the user does not get the benefit of real-time alerts, summary reports, or assistive diagnoses. However, with the proposed and implemented heart attack detection algorithm, it is possible to perform real-time beat analysis and provide assistive diagnosis. After an assistive diagnosis is made, the optimum alerts and telemedicine functionalities are needed to provide real-time feedback, which will be described in this chapter.

5.1 PROPOSED ALERT AND TELEMEDICINE WARNING SYSTEM

A system of multilayered levels of alerts and telemedicine functions will be implemented when an ST episode occurs that is capable of alerting the user, a designated point of contact (POC), and upload the abnormal ECG data using a telemedicine service. Having a multilayer system of

alerts provides redundancy and therefore, added assurance that should a heart attack occur the system will be able to notify either the user or a POC.

The flow of events for the warning system is given in Figure 18. In the event of ST segment elevation the ECG signal will be recorded and uploaded to a telemedicine service. Not only does this allow the user's doctor the ability to view the ECG in real time, but documents ST elevation episodes, which would otherwise go unreported. Having a history of cardiac events could be useful in assessing overall cardiac health. While ECG is streaming to the database, the user is simultaneously alerted via the native smartphone capabilities (i.e. audible, vibratory and pop-up alerts). Given the urgency of heart attack, this alert may not be sufficient. Therefore, if the user does not acknowledge the alert for whatever reason (e.g. incapacitated), a second level of alerts will be dispatched. A pre-arranged POC will be notified via text message or email that the user could be experiencing a heart attack and is not responding to the alert. This message will be supplemented by providing the GPS location of the user in the event they cannot be reached by the POC. While 911could be notified, it is believed that having an assigned POC is a more practical solution for an assistive device due to liability concerns.
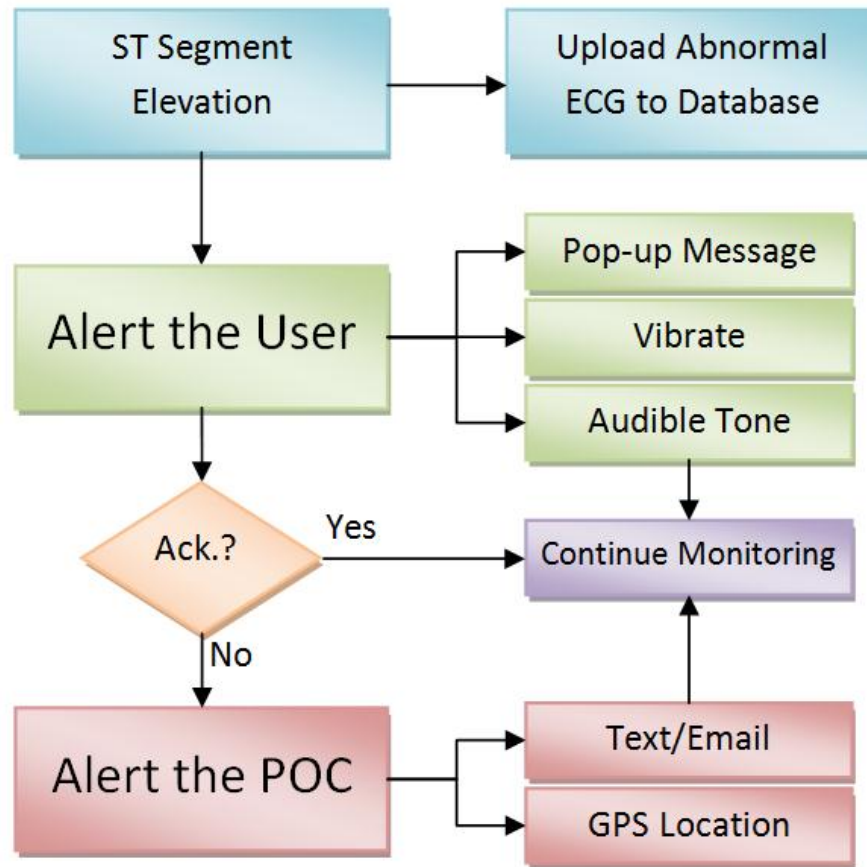
Figure 18. Heart Attack Warning and Telemedicine Workflow

5.2   IMPLEMENTATION

The previously described multilayer alert and telemedicine warning system was implemented on the *HeartToGo* platform on a Windows Mobile 6 smartphone. It consists of a telemedicine service, user alerts, and point of contact alerts.

5.2.1   Telemedicine service

Smartphones, whose primary role is communication, have the intrinsic ability to share data. When ST episodes occur they need to be: 1) documented for medical history and 2) the abnormal ECG needs to be recorded for review by a cardiologist for a definitive diagnosis. To implement this telemedicine function, email was used as a proof of concept. Modern smartphones can send and receive emails over their connection to wireless providers or through Wi-Fi, thus making them capable of sending and receiving anytime they are in range of cell tower or wireless router. A buffer is used to accumulate ECG data in five-minute intervals and is then sent to a predefined email address. In the future, a more elaborate telemedicine system could be implemented that interfaces with existing hospital protocols, but currently is beyond the scope of the proof of concept prototype presented in this research.

5.2.2   User alerts

As shown in Figure 18, the first level of alerts is the user alert. The smartphone is an ideal platform to implement such an alert because they are designed to notify their users of events. The smartphone implementation takes full advantage of all of the native smartphone alert features. When at ST episode occurs, the user is provided with an audible, vibratory, and pop-up alert. The pop-up alert is shown in Figure 19 and states that an ST episode was detected and that they have a certain amount of time remaining to acknowledge the alert before the POC is notified. The countdown timer is implemented using the standard time libraries made available by Windows Mobile 6. Furthermore, this alert is implemented on its own dedicated thread to allow the heart attack detection algorithm to continue processing ECG data.
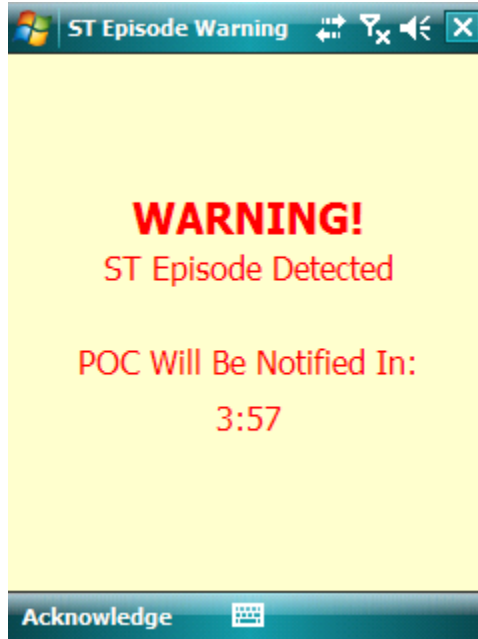
Figure 19. Heart Attack Warning for the User

5.2.3   Point of contact alerts

In the event that the user does not acknowledge their ST episode alert, for whatever reason (e.g. incapacitated, sleeping), the POC will receive an alert. This alert is predefined to be sent by email or by text message to either an email address or to another smartphone as a text message. The advantage of providing the ability to send messages via email or text is that a PDA, which the application is capable of running on, may not have a cellular network connection, but only be able to communicate using Wi-Fi, i.e. email. In this situation, despite being able to only send warnings through email, they could still be received as a text message by taking advantage of cellular service providers' features of being able to email a text message. For example, sending an email to 8145551234@att.txt.net would be translated from a text message to an email by ATT's server and arrive as a text message on 814-555-1234. Of course, it is more

straightforward when using smartphones instead of PDAs, since smartphones have a cellular network connection and can send normal text messages.

In addition to sending a text-based alert to the POC, the user's GPS coordinates are included with the message in the event the POC needs to know their location. Windows Mobile 6 provides an intermediate layer between the GPS hardware and the application layer to make use of the GPS. To obtain the GPS coordinates the following steps were taken:

1. Enable GPS

2. Poll until a GPS location could be determined from the satellites

3. Disable GPS

Obtaining GPS coordinates is not an instant process. On the smartphone it took at least fifteen seconds for the phone to obtain a GPS position. This time can be increased if satellite view is obstructed. Therefore, this process runs on a separate thread so it does not tie up the ECG monitoring thread. Furthermore, in the case of a battery-powered device, it is critical to disable the GPS at the end of the sequence, as using GPS is power-hungry.

Figure 20 shows a sample email warning sent to a POC. Note that the email includes the telephone number that the user can be reached at as well as their GPS location. The GPS location is formatted for use with Google Maps for this prototype. This makes it easy to view the user's location – just click on the link. Similarly, a text-based alert is shown in Figure 21. Note that the same information (phone number and GPS location) is included in the text alert. Furthermore, the location hyperlink again opens in Google Maps on the mobile platform.
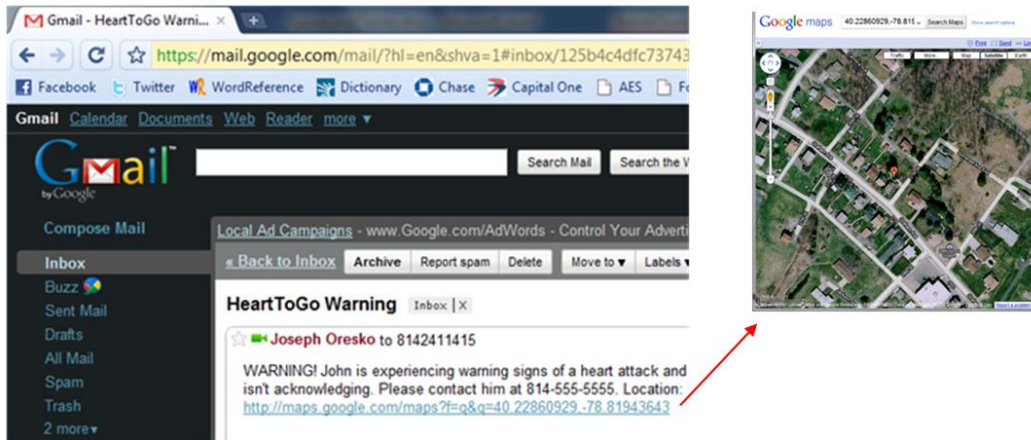
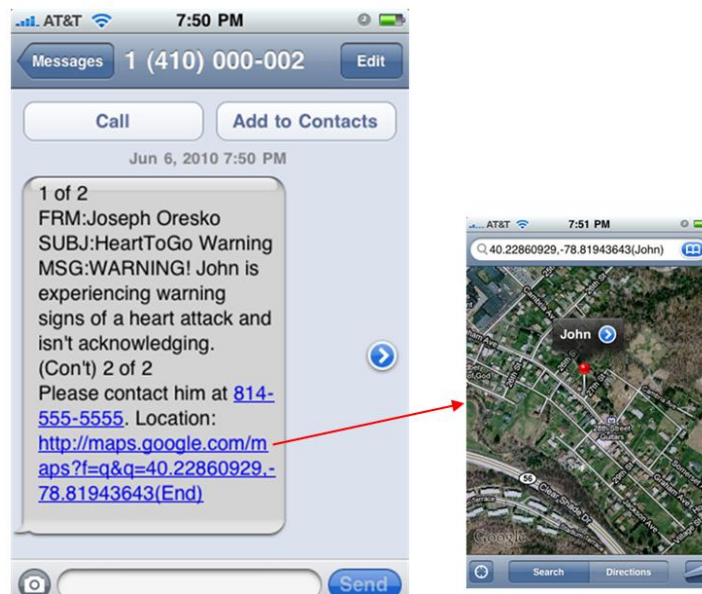**Figure 20.** Emailed Heart Attack Warning to the POC

Figure 21. Text Message Heart Attack Warning to the POC

6.0 STREAMING DATABASE VERIFICATION & WORKLOAD ANALYSIS

Product development is not complete when the implementation is finished. Only after a series of exhaustive tests should a product be deemed ready for use. This is especially true with medical devices, whose failure can result in loss of life. This chapter will describe the careful attention given to the challenge of testing the heart attack detection algorithm and warning system.

6.1 MOTIVATION

For a successful accurate, real-time ECG monitoring system the processing deadlines must be met and the algorithms must function correctly. The popular offline analysis methods run on PCs for ECG processing have no real-time deadlines and occupy only a small memory footprint on PCs. With respect to PCs, while smartphones have processing power making them capable of running demanding applications such as video and voice, their processors are much slower and their memory is smaller and slower than PCs. Therefore, for smartphones, like for any embedded platform, testing must be performed to verify that real-time deadlines are met. Furthermore, with a smartphone that is capable of running multiple time-shared applications at a time, it is critical to understand the effect of multitasking while performing ECG analysis on the fly.

Furthermore, while algorithms can be verified offline, the system as a whole needs to be verified. Validating a system designed to detect heart attacks is problematic because a test

subject experiencing a heart attack would need to be used – this is not practical. However, expertly annotated databases, such as the European ST database [24] from Physionet [25], contain ST episodes that if streamed to the phone could simulate a person having a heart attack. Therefore, it is necessary to provide a framework for extracting the data from the annotated database and using it to verify the heart attack detection and warning system in real time.

6.2   IMPLEMENTATION

Aside from testing with patients experiencing a heart attack – which is clearly not practical – the second best approach to testing this system is to use an expertly annotated database. This research proposes the novel idea of using a host PC to parse the database into the same format that the heart monitor uses to transmit data to the phone for real-time testing. This method has two advantages: 1) real data is used and 2) the use of the streaming database is transparent to the smartphone.

To accomplish this task, MATLAB is used as the framework for streaming the database. As previously mentioned, the heart monitor communicates with the phone via Bluetooth. On a PC, writing to a Bluetooth device is exactly like writing to a serial port, i.e. when writing to Bluetooth a virtual communications port is being used. MATLAB has built-in functions for writing to serial ports, which helped speed up the process of creating the serial port object.

The workflow for the streaming database is shown in Figure 22. First, the host PC and smartphone are paired – this is handled by Windows Mobile 6. Next, MATLAB opens the virtual serial port and creates the Bluetooth socket. Samples from the database are then parsed, framed, and sent out as a packet. Next, there is a delay by the sampling period so the ECG is sent at the

proper real-time sampling rate. This process of streaming data continues until the end of file (EOF).
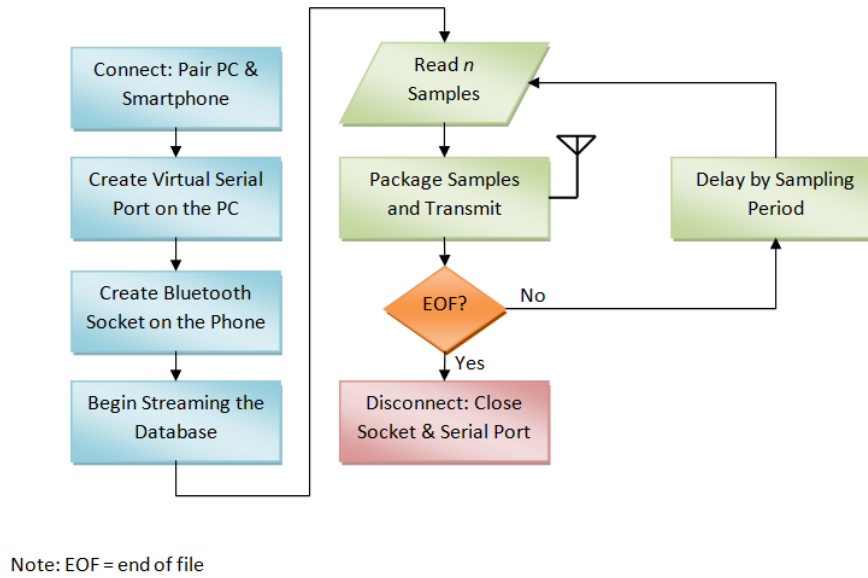

Figure 22. Database Testing Workflow

6.3 REAL-TIME VERIFICATION

Using the streaming database application, the annotated test data used to verify the algorithm and presented in chapter 4 section 3.1 was streamed to the phone in real time. All ST episodes were detected in real time and zero false positives were reported. Figure 23 highlights that the number of ST episodes is available in the cardiac summary report, which is updated as soon as the ST episode occurs. Furthermore, the warning system presented in chapter 5 was validated. The telemedicine service correctly transmitted the abnormal ECG data to the predefined database and the user- and POC-level alerts work as designed. Furthermore, the GPS location feature provided the correct location for the user.
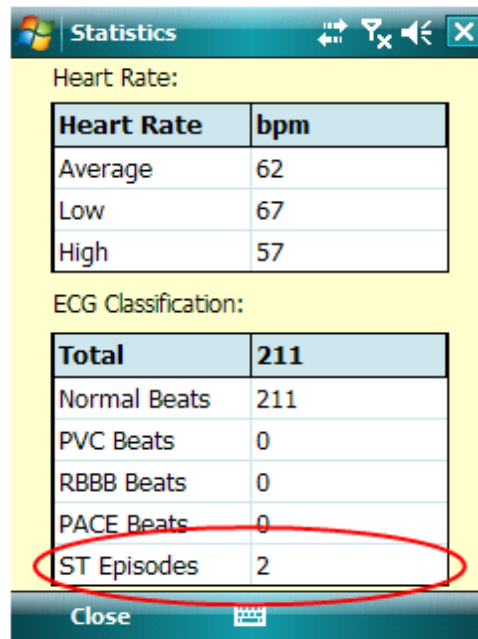
Figure 23. Statistics for Detected ST Episodes

6.4   WORKLOAD ANALYSIS

For medical applications, proper functionality is critical. Under ideal conditions, the heart attack detection algorithm has proven to run without error. However, it is important to consider the effects of testing in a real phone environment. To simulate this environment, normal phone tasks will be performed while the heart attack detection algorithm is running in the background. As the number of applications being multitasked is increased, the real-time deadlines of the heart attack detection algorithm will be strained.

6.4.1   Memory Usage

Modern PCs have seemingly limitless RAM – upwards of 32 GB in high end machines – however, modern smartphones are constrained to only a few hundred MB of RAM or less. The heart attack detection algorithm was initially prototyped on a PC and while steps were taken to ensure it is lightweight, the memory footprint needs to be investigated on the target smartphone platform. The streaming database method previously described is used for this task.

While streaming ECG data to the phone via Bluetooth, the memory footprint of *HeartToGo*, the application for data acquisition, display, heart attack detection, and warning was measured. Windows Mobile 6 provides a built-in memory manager, similar to a task manger on a PC. While running other commonly used applications, the RAM usage of the smartphone was measured, as shown in Figure 24. As shown, even when running *HeartToGo* and five other commonly used applications about 2/3 of the memory is free. Furthermore, almost 1/3 of the used memory is being tied up by the operating system. Therefore, it is safe to conclude that *HeartToGo* does not overburden the smartphone memory. Furthermore, Figure 25 compares the RAM usage of *HeartToGo* to other common applications. While it occupies the most RAM, it is on the same order of magnitude as other common applications, such as maps and internet browsing.
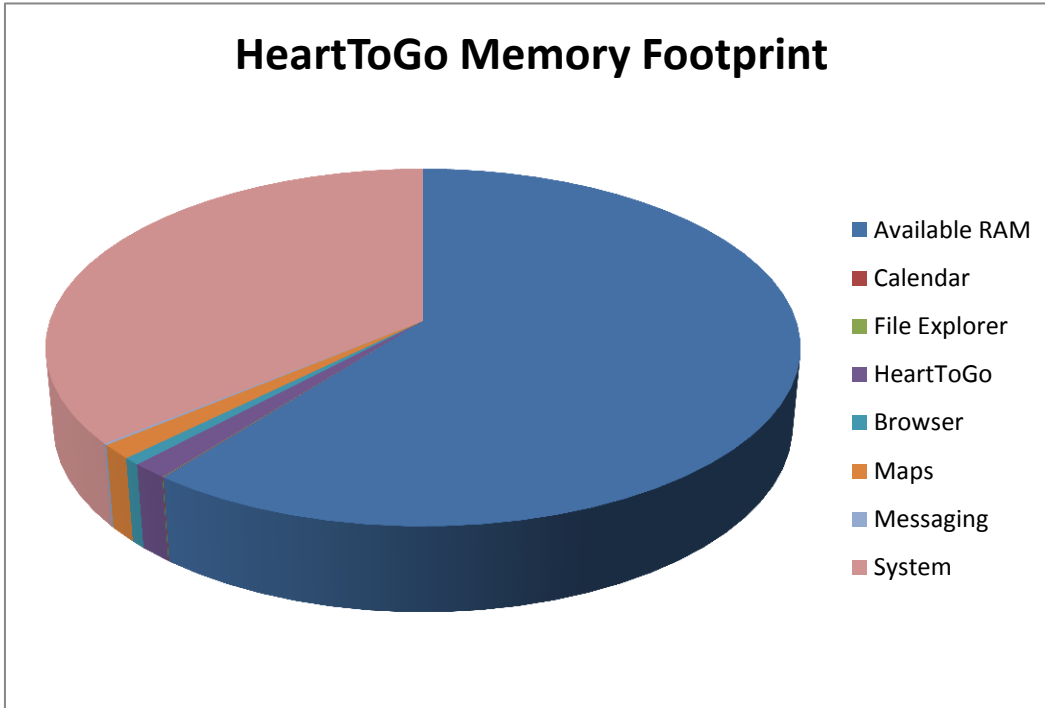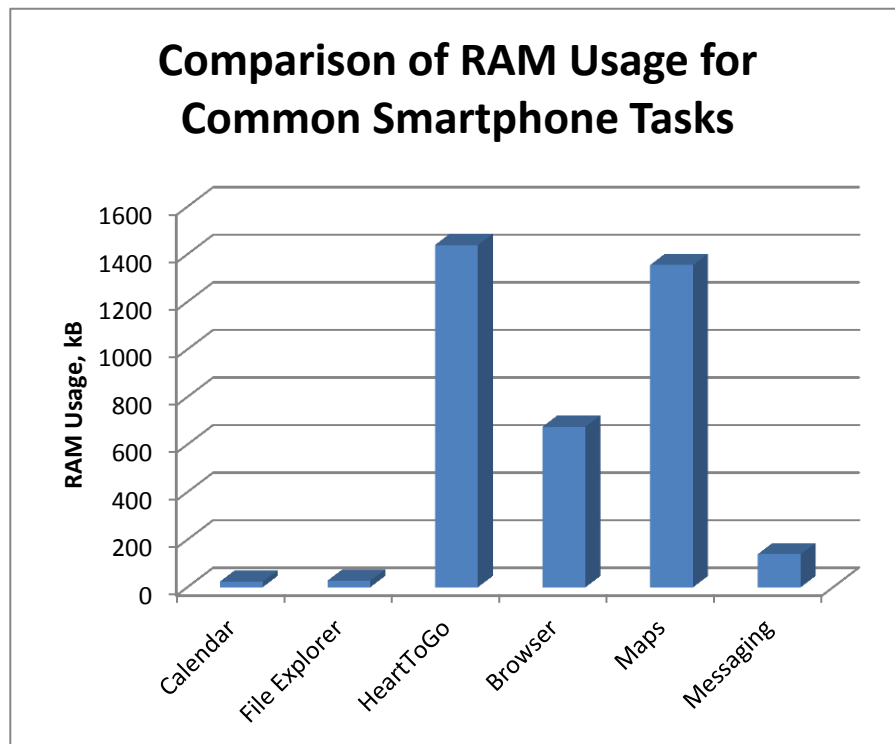
Figure 24. Heart Attack Detection Memory Footprint

Figure 25. Comparison of RAM Usage for Common Smartphone Tasks

7.0   CONCLUSION

7.1   THESIS SUMMARY AND CONCLUDING STATEMENTS

In this thesis, heart attack detection by smartphone ECG processing was realized, thus uniting the portability of Holter monitors with the real-time processing of resting ECG machines. By proposing and implementing an accurate, real-time, context-aware heart attack detection algorithm, a high classification accuracy of 96% was achieved. Furthermore, all ST episodes were detected by the algorithm and zero false positives were reported during testing with expertly annotated data.

Traditional smartphone alerts such as pop-ups, audible tones, and vibrations were used to provide real-time heart attack detection feedback. In addition, a more complicated layer of alerts was added in case the user is incapacitated, or otherwise incapable of acknowledging the alerts. A text message or email is sent to a designated POC, alerting them that the user is experiencing heart attack warning signs and is not acknowledging the warning. Furthermore, the precise GPS location of the user is sent to the POC, along with their telephone number in the case that they need immediate aid.

Finally, the lack of being able to test the system with a heart attack from the user was overcome by using an expertly annotated database that was streamed to the phone in real time in place of wearing the ECG sensor. This process has the advantage of not only being transparent to

the heart attack processing algorithms, but also allows the software to run exactly as it would with the sensor for workload testing.

While it is acknowledged that the prototype presented is not a replacement for the Holter monitor or the resting ECG, it does serve as a powerful assistive diagnosis tool. Furthermore, it provides another source of feedback for monitoring the heart. With this system, not only does the user need to rely on symptoms such as chest pain, which may or may not occur prior to a heart attack, but additionally, the user's heart is continuously being monitored for an abnormal ECG. As smartphones continue to become faster, more ECG processing features can be added to this proof-of-concept framework to provide a complete heart monitoring system-- capable of saving lives.

7.2   FUTURE WORK

The smartphone prototype described in this thesis is capable of providing assistive diagnosis for heart attack via smartphone ECG processing. However, as previously stated, not all heart attacks are detectable. Advancement in the wearable ECG sensor could incorporate more leads to provide a better view of the heart from different directions, thus allowing for additional heart attacks to be detected. Furthermore, additional leads would help to eliminate false positives and provide a more sound predictive diagnosis, due to the redundancy. Additionally, multiple leads would allow for the incorporation of reciprocal ST segment depression detection, to aid in heart attack detection.

With the advent of multi-core processors in PCs, it is only a matter of time before they make their way into the smartphone market. The most challenging aspect of multi-core

processors is to utilize them efficiently. This requires software that takes advantage of the multi-core architecture. Therefore, parallelizations should be performed on the ECG processing code to take advantage of concurrency. These optimizations would aid in the future performance of the program on multi-core phones. Improving performance is important because it helps to meet the critical real-time processing deadlines and allows for additional functionality, e.g. multiple leads and the detection of additional CVDs.

Finally, a framework was developed for testing the heart attack detection algorithm in real time while running on the phone. While expertly annotated data were located, which is hard to come by, and used for validation, the use of additional test data from a wide variety of patients with different conditions is recommended, under the supervision of experienced cardiologists. Also, a database containing accelerometer data is desirable to aid in determining what threshold (or other method) should be used when adding context awareness.

BIBLIOGRAPHY

[1] D. Lloyd-Jones, *et al.*, "Heart disease and stroke statistics 2009 update. A report from the American Heart Association statistics committee and stroke statistics subcommittee," *Circulation*, vol. 119, no. 3, pp. e21-e181, Jan. 2009.

[2] Wall Street Journal, "For Men at 40, Risk of Cardiac Death 1 in 8," http://online.wsj.com/article/SB125833149978449651.html

[3] M. Gertsch, *The ECG Manual*. London: Springer-Verlag, 2009.

[4] M. Khan, *Rapid ECG Interpretation,* Totowa, NJ: Humana Press Inc., 2008.

[5] B. Surawicz and T. Knilans, *Chou's Electrocardiography in Clinical Practice*. Philadelphia: Saunders Elsevier, 2008.

[6] S. Chugh, *Textbook of Clinical Electrocardiography*, Tunbridge Wells, UK: Anshan Ltd., 2006.

[7] J. Oresko, Z. Jin, J. Cheng, S. Huang, Y. Sun, S. Duschl, and A. Cheng, "A Wearable Smartphone-based Platform for Real-Time Cardiovascular Disease Detection via Electrocardiogram Processing," *IEEE Trans. on Information Technology in Biomedicine,* vol. 14, no. 3, pp. 734-740, May 2010.

[8] J. M. Cano-García, E. González-Parada, V. Alarcón-Collantes, and E. Casilari-Pérez, "A PDA-based portable wireless ECG monitor for medical personal area networks," in *Proc. IEEE MELECON*, Benalmádena, Spain, 2006, pp. 713-716.

[9] W. Chung, C. Yau, K. Shin, and R. Myllyla, "A cell phone based health monitoring system with self analysis processor using wireless sensor network technology," in *Proc. 29th IEEE EMBC*, Lyon, France, 2007, pp. 3705-3708.

[10] T. Lee, J. Hong, and M. Cho, "Biomedical digital assistant for ubiquitous healthcare," in *Proc. 29th IEEE EMBC*, Lyon, France, 2007, pp. 1790-1793.

[11] X. Chen, C. T. Ho, E. T. Lim, and T. Z. Kyaw, "Cellular phone based online ECG processing for ambulatory and continuous detection," *Computers in Cardiology*, vol. 34, pp. 653-656, Sept. 2007.

[12] K. Goh, J. Lavanya, Y. Kim, E. K. Tan, and C. B. Soh, "A PDA-based ECG beat detection for home cardiac care," in *Proc. 27th IEEE EMBC*, Shanghai, 2005, pp. 375-378.

[13] J. Rodríguez, A. Goni, and A. Illarramendi, "Real-time classification of ECGs on a PDA," *IEEE Trans. Info. Tech. in Biomed.*, vol. 9, no. 1, pp. 23-34, Mar. 2005.

[14] Z. Jin, Y. Sun, and A. Cheng, "Predicting Cardiovascular Disease from Real-Time Electrocardiographic Monitoring: An Adaptive Machine Learning Approach on a Cell Phone," in *Proc. 31st IEEE EMBC*, Minneapolis, MN, 2009, pp. 6889–6892.

[15] Philips Medical Systems, "ST/AR: ST segment and arrhythmia monitoring," *Clinical Measurements Datasheet*, April, 2004.

[16] X. Li, et al., "ST-T complex automatic analysis of the electrocardiogram signal based on wavelet transform," in *Proc. 29th IEEE Bioengineering*, 2003, pp. 144-145.

[17] C. Papaloukas, D. I. Fotiadis, A. Likas, A. P. Liavas, and L.K. Michalis, "A knowledge-based technique for automated detection of ischemic episodes in long duration electrocardiograms," *Med. Biol. Eng. Comput.*, vol. 39, pp. 105–112, 2001.

[18] T. Stamkopoulos, et. al., "ECG analysis using nonlinear PCA neural networks for ischemia detection," *IEEE Trans. on Signal Processing*, vol. 46, no. 11, pp. 3058-3067, Nov. 1998.

[19]   F. Badilini, et al., "Beat-to-beat quantification and analysis of ST displacement from Holter ECGs: a new approach to ischemia detection," in *Proc. Computers in Cardiology*, Durham, NC, 1992, pp. 179-182.

[20]   Fischell, et al., "System for the detection of cardiac events," United States Patent, US 669023B1, Aug. 19, 2003.

[21]   G. Jeong and K. Yu, "Morphological classification of ST segment using reference STs set," in Proc. *29th IEEE EMBS*, Lyon, France, 2007, pp. 636-639.

[22]   C. Papaloukas, et al., "A robust knowledge-based technique for ischemia detection in noisy ECGs," in *Proc. Knowledge-Based Intelligent Engineering Systemsand Allied Technologies*, Brighton, 2000, pp. 768-771.

[23]   M. Raya, et al., "Adaptive noise cancelling of motion artifact in stress ECG signals using accelerometer," in Proc. *2nd Joint EMBS/BMES*, Houston, 2002, pp. 1756-1757.

[24]   A. Taddei, et al., "The European ST-T database: development, distribution, and use," *Computers in Cardiology*, pp. 177-180, 1990.

[25]   A. L. Goldberger, et al., "PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. e215-e220, June 2000.

[26]   P. Hamilton, "Open source ECG analysis," *Computers in Cardiology*, vol. 29, no. 1, pp. 101–104, Sept. 2002.

[27]   J. Pan and W. Tompkins, "A real-time QRS detection algorithm," *IEEE Trans. Biomed. Eng.*, vol. BME-32, no. 3, pp. 230-236, Mar. 1985.

[28]   P. S. Hamilton and W. J. Tompkins, "Quantitative investigation of QRS detection rules using the MIT/BIH arrhythmia database," *IEEE Trans. Biomed Eng.*, vol. BME-33, no. 12, pp. 1157-1165, Dec. 1986.

[29]   R. Duda, P. Hart, and D. Stork, *Pattern Classification*, John Wiley & Sons, Inc.: New York, 2001.

[30]   Y. Goletsis, C. Papaloukas, D. I. Fotiadis, A. Likas, and L. K. Michalis, "Automated ischemic beat classification using genetic algorithms and multicriteria decision analysis," *IEEE Trans.Biomed. Eng.*, vol. 51, no. 10, pp. 1717–1725, Oct. 2004.

[31]   C. Papaloukas, D. I. Fotiadis, A. Likas, and L. K. Michalis, "An ischemia detection method based on artificial neural networks," *Artif. Intell. Med.*, vol. 24, no. 2, pp. 167–178, 2002.

[32]   R. V. Andreao, S. M. T. Muller, J. Boudy, B. Dorizzi, T. F. Bastos Filho, and M. Sarcinelli Filho, "Incremental HMM training applied to ECG signal analysis," *Comput. Biol. Med.*, vol. 38, pp. 659–667, 2008.

[33]   F. Jager, G. B. Moody, and R.G. Mark, "Detection of transient ST segment episodes during ambulatory ECG monitoring," *Comput. Biomed. Res.*, vol. 31, no. 5, pp. 305–322, 1998.

[34]   N. Maglaveras, T. Stamkopoulos, C. Pappas, and M. G. Strintzis, "An adaptive backpropagation neural network for real-time ischemia episodes detection: Development and performance analysis using the European ST–T database," *IEEE Trans. Biomed. Eng.*, vol. 45, no. 7, pp. 805–813, Jul. 1998.