Electrocardiogram Signal Quality Analysis to Reduce False Alarms in Myocardial Ischemia Monitoring

by

Mohamed Abdelazez

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Abstract

The probability of myocardial ischemia, reduction in blood flow to the heart muscle, is increased following a non-cardiac surgery, which can lead to an increase in the incidence of post-operative heart attacks, cardiac death, and increase in hospital length of stay among patients. β -Blockers can be administered to reduce the probability of experiencing a cardiac event post a non-cardiac surgery; however, they have side effects including stroke, bradycardia, hypotension, morbidity, and mortality. Myocardial ischemia causes a deviation of ST segment in the electrocardiogram (ECG), which can enable targeted administration of β -Blockers rather than prophylactic administration; however, attempts to utilize ECG as a diagnostic tool in real-time were hindered by a large number of false alarms due to noise and error in the quantification of ST segment deviation. The objective of this thesis is to develop a system to gate false alarms using the signal quality of the ECG and quality of the ST segment deviation estimate. The system was tested using ECG records from Physionet's Long-Term ST Database (LTSTDB) that were contaminated with motion artifact noise from Physionet's MIT-BIH Noise Stress Test Database (NSTDB). The system based on signal quality and ST segment trend estimation gated 100% of noise-induced alarms (86% of all false alarms) attaining a recall and precision of 0.72 and 0.73, respectively, marking an increase of 0.42 in precision and a decrease of 0.05 in recall from the commercial bedside monitor baseline performance (precision – 0.31, recall - 0.78). The signal quality analysis approach to gate contaminated data was extended to an ECG biometrics system. The signal quality analysis led to the rejection of 193 (57.8%) out of 334 false identifications at the loss of 25 (8.14%) out of 307 true identifications.

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Statement of Originality

This thesis presents the work of the author, under the supervision of Dr. Adrian Chan and Dr. Homer Yang, completed at Carleton University for the degree of M.A.Sc. in Biomedical Engineering. The work presented in Chapter 4 was based on a signal quality algorithm developed by Patrick Quesnel. The development of the false alarm gating system, the subsequent ST segment deviation trend estimator algorithm and the exploration of the application of signal quality analysis in biometrics systems were performed by the author. The work presented in the thesis was reviewed by Dr. Adrian Chan and Dr. Homer Yang. Portions of this thesis were presented in a journal paper summarized below.

Mohamed Abdelazez, Patrick X. Quesnel, Adrian D. C. Chan, and Homer Yang, “Signal Quality Analysis of Ambulatory Electrocardiograms to Gate False Myocardial Ischemia Alarms,” accepted to *IEEE Transactions on Biomedical Engineering*, Aug. 2016.

This journal paper described the development of the false alarm gating system presented in Chapter 4. Patrick X. Quesnel developed the SQI generation algorithm employed by false alarm gating system and preliminary investigation of the alarm gating system. The author developed the false alarm gating algorithm SQV_{SEN} and performed verification and testing on a large data set available from Physionet. The manuscript was written under the guidance of Dr. Adrian Chan and Dr. Homer Yang. The manuscript was revised following feedback from the co-authors and was prepared for publication by the author. The paper was accepted in IEEE Transactions on Biomedical Engineering following the peer-review process on August 11, 2016.

Table of Contents

Abstract.....	ii
Statement of Originality	iv
Table of Tables	vii
Table of Figures	ix
List of Abbreviations	xiii
1 Chapter: Introduction	1
1.1 Thesis Objectives	3
1.2 Contributions	3
1.3 Thesis Outline	5
2 Chapter: Background and Literature Review	7
2.1 Cardiovascular System	7
2.2 Myocardial Ischemia	8
2.3 Electrocardiogram (ECG).....	9
2.4 PeriOperative Ischemic Evaluation (POISE).....	18
2.5 PeriOperative Ischemia Reduction Studies (PROSE).....	20
2.6 Signal Quality Analysis.....	23
2.7 Gating Alarms Using SNR-Based SQI	27
2.8 Current State of Automated Estimation of ST segment	27
2.9 Summary	28
3 Chapter: Methodology	30
3.1 Proposed System Overview	30
3.2 Data Set	31
3.3 Test Apparatus and Software.....	35
3.4 Signal Quality Index (SQI) Generation.....	38
3.5 Alarm Generation Criteria and Implementation	42

3.6	Gold Standard	46
3.7	Test Signals Generation.....	46
3.8	Test Procedure	49
3.9	Analysis.....	50
4	Chapter: Development and Testing of SQVS _{EN}	52
4.1	System Overview	52
4.2	System Performance	55
4.3	Investigation of Misidentification of Fiducial Points.....	63
4.4	Summary	66
5	Chapter: Gating False Alarms Generated by Misidentified Fiducial Points.....	68
5.1	Development of ST segment Deviation Trend Estimation Algorithm.....	68
5.2	Gating False Alarms in Unaltered LTSTDB Records.....	77
5.3	Integrating Trend Estimator with SQVS _{EN}	84
5.4	Summary	85
6	Chapter: Application of Signal Quality Analysis in an ECG Based Biometric System.....	87
6.1	Methodology.....	88
6.2	Results and Discussion.....	93
6.3	Summary	98
7	Chapter: Conclusions and Future Work	99
7.1	Conclusions	99
7.2	Future Work.....	101
	References	104

Table of Tables

Table 3.1 ECG recordings used in the study and their durations	33
Table 3.2 Alarm generation criteria.....	42
Table 3.3 Detailed description of the FSM transitions and the timers	45
Table 4.1 Detailed description of the FSM transitions and the timers with the addition of the SQI condition which enabled/disabled the FSM	54
Table 4.2 Comparing the TPs, FNs, FPs, and TNs detected in the unaltered signals and the test signals with no gating applied	57
Table 4.3 Comparing the TPs, FNs, FPs, and TNs detected in the test signals and the test signals with gating applied at 6 dB.....	58
Table 4.4 Comparing the TPs, FNs, FPs, and TNs detected in the unaltered signals and the test signals with gating applied at 6 dB	59
Table 5.1 Comparing the TPs, FNs, FPs, and TNs detected in the unaltered signals and the unaltered signals with gating applied at 0.3778 using Pearson Correlation Coefficient ...	79
Table 5.2 Comparing the TPs, FNs, FPs, and TNs detected in the unaltered signals and the unaltered signals with gating applied at 0.3778 using Kendall rank correlation	80
Table 5.3 Comparing the TPs, FNs, FPs, and TNs detected in the unaltered signals and the unaltered signals with gating applied at 0.3778 using Spearman rank correlation	81
Table 5.4 Comparing the TPs, FNs, FPs, and TNs detected in the test signals and the test signals with gating applied at 6 dB using SQIs and 0.3778 using Spearman rank correlation	85
Table 6.1 Number of recordings per subject.....	90

Table 6.2 Comparing the TPs, FPs, and TNs detected in no gating case and with gating applied at 1 dB.....95

Table of Figures

Figure 2.1 Anatomy of the heart with major structures labeled including both ventricles, right atrium and coronary arteries [25].	8
Figure 2.2 A typical ECG waveform with PQRST waves and the intervals between the waves labeled [34].	10
Figure 2.3 The placement of the 10 wires on the body to record 12 lead ECG [35]	11
Figure 2.4 Projections of the ECG leads in the sagittal, frontal and transverse planes of the body [23].	12
Figure 2.5 a) a normal ST segment, b) an ischemic ST segment. ECG was taken from record 's20011' from Physionet Long-Term ST Database [43], [44]	17
Figure 2.6 Illustration of existing monitoring system employed at TOH and the PROSE white box solution (custom monitoring system) as presented in [8].	21
Figure 3.1 Block diagram of the proposed system showing the route taken by the ECG signal from the wireless ECG transmitter to the commercial bedside monitor where the ST segment is analyzed for deviation. The quality analyzer, encased by the dashed line, is running in parallel to the ST analysis system and disables the alarm generating an algorithm based on a signal quality index (SQI) and the ST trends correlation. The shaded elements were implemented in [8] as an alarm delivery system to clinicians but are not used in this study.	31
Figure 3.2 Five seconds of synthetic ECG generated using ecgsyn at 90 beats per minute	35
Figure 3.3 91369 Ultraview SL Bedside Monitor manufactured by SpaceLabs	36

Figure 3.4 Ultraview Digital Telemetry Multiparameter Transmitter 90345 manufactured by Spacelabs.....	36
Figure 3.5 Patient simulator MS400 manufactured by CONTEC Medical Systems	38
Figure 3.6 Identified R-Wave in a 5-second ECG segment using Pan-Tompkins algorithm. The top graph shows the R-wave on filtered QRS. The middle graph shows the R-wave on the squared signal. The last graph shows the pulse train on the unfiltered ECG signal....	39
Figure 3.7 Ensemble averaged 90 seconds of ECG data with added white gaussian noise generated using ‘wgn’ function available in MATLAB. The red line is the ensemble averaged beat.....	41
Figure 3.8 Finite State Element (FSM) implementation of alarm generation criteria	44
Figure 3.9 CONTEC’s Case Conversion GUI with parameters setup for test signals	48
Figure 3.10 definitions of TP, FP, and FN in the context of this study.....	51
Figure 4.1 TP, FP, and FN of all leads of all test signals vs. SQI threshold levels and FP count in unaltered signals.....	61
Figure 4.2 Precision Recall Curve showing Precision and Recall of the SQVS _{EN} alarm gating solution.....	61
Figure 4.3 ST segment deviation overestimation by bedside monitor (red) compared to GS (blue) taken from lead V2 of the record s20051. Alarm conditions are marked as solid black horizontal lines.	64
Figure 4.4 ECG sample from s20051 during the bedside monitor overestimation of ST segment deviation (please note that this is lead V2; therefore, the R-wave is pointing downwards).....	64

Figure 4.5 ST segment deviation measurement location user interface of Spacelab's bedside monitor.....	65
Figure 4.6 Deviation measurements history as provided by the bedside monitor	66
Figure 5.1 A sample beat from LTSTDB record 's20071' where the Q and S waves are highlighted in red, and the search window is marked by the hatched region.	69
Figure 5.2 A sample beat from LTSTDB record 's20071' where the ST segment is highlighted in red, the J point is marked by the black dot, and the search window is marked by the hatched region.	71
Figure 5.3 A sample beat from LTSTDB record 's20071' where the isoelectric line is highlighted in red, and the search window is marked by the hatched region.	72
Figure 5.4 Estimated trend of ST segment deviations for LTSTDB record 's20071' (black) compared to GS (blue).....	74
Figure 5.5 Pearson correlation coefficient of lead II per record for trend estimator (black) and bedside monitor (red) with the GS.....	75
Figure 5.6 Pearson correlation coefficient of lead V2 per record for trend estimator (black) and bedside monitor (red) with the GS. The error bars represent one standard deviation.	76
Figure 5.7 Comparison of the trend estimator measurements (black), bedside monitor measurements (red), and GS (blue) of the LTSTDB record 's20071'	77
Figure 5.8 TP, FP, and FN of all leads of all unaltered signals vs. absolute value of Spearman rank correlation threshold levels	82
Figure 5.9 Precision Recall Curve showing Precision and Recall of the unaltered signals alarm gating system based on absolute value of Spearman rank correlation	82

Figure 5.10 Example of bedside monitor measurements (red) slow drift outside of normal bounds while matching the trend of the estimated trend (black) and ultimately the GS (blue). This example is from lead V2 of LTSTDB record 's20211'.	83
Figure 5.11 Example of bedside monitor measurements (red) sudden jump outside of normal bounds while matching the trend of the estimated trend (black) and ultimately the GS (blue). This example is from lead II of LTSTDB record 's20061'.	84
Figure 6.1 BioRadio Wireless Physiology Monitor manufactured by Great Lakes NeuroTechnologies U.S.A. [67].	88
Figure 6.2 Custom pad with Ag/AgCl electrodes without conducting gel placed for collection of lead I of ECG	89
Figure 6.3 An ECG segment from the first standing step representative of the average SQI from subject 25 third recording (top left) and the preprocessed version of the segment (bottom left). The top right shows an ECG segment from the light movement step representative of the average SQI from subject 01 fourth recording while the bottom right shows the preprocessed version of the segment.	94
Figure 6.4 TP and FP of all segments vs. SQI threshold levels	96
Figure 6.5 Beat generated by ensemble average (blue) and template (red) from subject 17	97
Figure 6.6 ECG data for identification from subject 7 (blue), correct template from the database (black), and wrong template matched to the data according to the identification algorithm (red).	97

List of Abbreviations

ADC	Analog to Digital Converter
AECG	Ambulatory Electrocardiogram
AHA	American Heart Association
BPM	Beats Per Minute
DC	Direct Current
ECG	Electrocardiogram
ECRI	Emergency Care Research Institute
FN	False Negative
FP	False Positive
FSM	Finite State Machine
GS	Gold Standard
GUI	Graphical User Interface
HR	Heart rate
Hz	Hertz
LBBD	Left Bundle Branch Block
LTSDB	Long-Term ST Database
MSE	Mean Square Error
METs	Metabolic Equivalents
NSTDB	MIT-BIH Noise Stress Test Database
POISE	PeriOperative Ischemic Evaluation
PPV	Positive Predictive Value
PROSE	PeriOperative Ischemic Reduction Studies

SA	Sinoatrial
SL	Spacelabs
SD	Standard Deviation
SNR	Signal To Noise Ratio
SQI	Signal Quality Index
SQVS	Signal Quality Verification System
TN	True Negative
TOH	The Ottawa Hospital
TP	True Positive

1 Chapter: Introduction

Non-cardiac surgeries, such as knee or hip replacement, place the patient's body under tremendous stress due to post-surgical (trauma) inflammation, anesthesia, hypothermia, and pain [1]. The stress can lead to a reduction of blood flow to the myocardial tissue, heart muscle tissue, resulting in myocardial ischemia [1]. Myocardial ischemia is a known precursor of myocardial infarction or heart attack [2]. As many as 900,000 patients worldwide experiences cardiac events, such as cardiac death, non-fatal myocardial infarction, or heart attack due to non-cardiac surgeries [1]. These cardiac events increase the hospital length of stay, morbidity, and mortality of the patient [3], [4].

β -Blockers can be administered to reduce the probability of experiencing a cardiac event [5], [6]. β -Blockers are a class of medications that reduces the flight-fight response effect on the cardiac tissue [5]. Patients that have undergone a non-cardiac surgery may be prescribed β -Blockers, as a prophylactic treatment [6]. Even though β -Blockers are effective, a randomized controlled trial, titled PeriOperative Ischemic Evaluation (POISE), found β -Blockers to have various side effects, which are as severe as the aforementioned cardiac events [7]. These side effects include, but are not limited to, stroke, bradycardia, hypotension, other morbidities, and mortality [7].

A study, titled PeriOperative Ischemic Reduction Studies (PROSE), was established to investigate the effectiveness of selectively administering β -Blockers to patients deemed at risk of myocardial ischemia [8]. At-risk patients are identified by monitoring the electrocardiogram (ECG), the electrical activity of the heart, for signs of myocardial

ischemia [8]. Patients are evaluated prior, during, and following surgery, which is known as perioperative patient management [9]. Before surgery, patients are evaluated based on their metabolic equivalents (METs), which are the resting or basal oxygen consumption of a 40-year-old 70 kg male [9]. Patients found to have less than 4 METs, inability to climb more than two flights of stairs, are recommended for an exercise ECG test to evaluate their cardiac health and are monitored for any signs of myocardial ischemia [9]. ECG is also used during and after the surgery to detect any evidence of myocardial ischemia [9]. A cardiologist typically analyzes the ECG after the test; however, as with any medical condition, early intervention is considered crucial to increase the chances of mitigating the damage caused [10], [11]. Real-time automated myocardial ischemia monitoring was introduced in patient monitoring to expedite the time for intervention to reverse the ischemic cascade and prevent any damage to the cardiac tissue [11]. However, real-time automated monitoring of myocardial ischemia has been plagued with issues and in many cases is not utilized by clinicians [11]. PROSE found that the movement of patients led to false alarms [8].

A false alarm is the false detection of signs of a medical condition resulting in an alert (e.g., the sounding of an audible alarm). Medical alarms are used to notify clinicians of a situation requiring immediate attention such as cardiac arrest; therefore, they are an integral part of the medical environment. Constant exposure to alarms, including false or minor alarms, can lead to desensitization condition found in clinicians known as alarm fatigue [12]. Alarm fatigue is one of the conditions known as alarm hazards which has been recognized by the Emergency Care Research Institute (ECRI) [13]. ECRI declared alarm hazards as

the top patient safety hazard for the years 2012 to 2015 [14]-[17]. Mitigation of false alarms will lead to a reduction of patient hazards, improvement of perioperative care, and an increase of confidence in automated myocardial ischemia monitoring systems.

1.1 Thesis Objectives

The objectives of the thesis are the following:

1. Develop a system to gate false alarms produced by low ECG signal quality. The system will employ a Signal Quality Index (SQI) to quantify the ECG signal quality and gate alarms. The performance of the system will be evaluated.
2. Develop an algorithm to gate false alarms generated due to the poor estimates of the ST deviation caused by misidentification of fiducial points in ECG signal. The performance of the algorithm will be evaluated.
3. Explore the application of signal quality analysis of ECG in the field of biometrics to gate ECG contaminated with noise and/or artifacts. The performance of the algorithm will be evaluated.

1.2 Contributions

The work presented in the thesis resulted in three main contributions:

- 1. Development of a false alarm gating system based on ECG signal quality analysis and performance evaluation of the system**

Previous work has shown that the signal to noise ratio can be used as a representative of signal quality [18], [19]. A solution utilizing signal to noise ratio as a signal quality index to gate false alarms was introduced in [18]. In this thesis,

the system was developed and tested on an expanded data set with randomized added noise to better represent patient ambulation. The gating system increased the precision of the commercial bedside monitor by 0.26 (from 0.31 to 0.58) at a reduction of 0.01 (from 0.78 to 0.77) in the recall. The gating system gated 100% of the noise induced alarms (68% of all of the false alarms) at the loss of a single true alarm out of 77 true alarms.

The signal quality analysis algorithm discussed and utilized by the system developed in this thesis was developed in collaboration with Patrick Quesnel, author of [18], and the results were presented in [19] at the World Congress on Medical Physics and Biomedical Engineering 2015 by the thesis's author; however, the contribution of thesis's author was not major and therefore, not be listed as a contribution.

2. Development of a false alarm gating algorithm based on ST segment deviation trends and performance evaluation of the algorithm

It was found that false alarms can be generated due to the myocardial ischemia monitoring system misidentifying the fiducial points in the ECG signal, leading to overestimation of the ST segment deviation [18]. In this thesis, an algorithm is proposed to estimate the ST segment deviation trend and provide insight into the trend of the changes in the deviation. The algorithm is then used in conjunction with the ST segment deviation estimates from the myocardial ischemia monitoring bedside monitor to gate false alarms. The algorithm was integrated with the ECG

signal quality analysis system developed as part of the first contribution and the resulting system gated 85% of all of the false alarms at the loss of six true alarms out of 77 true alarms. It increased the precision of the commercial bedside monitor by 0.41 (from 0.31 to 0.72) at a reduction of 0.06 (from 0.78 to 0.72) in the recall.

3. Exploration of the application of signal quality analysis in biometrics:

The global trend is to move away for typical alphanumeric passwords toward more robust biometrics based on unique properties of the human body [20]. As an example, fingerprints, iris recognition, face recognition and palm print have been used in the past to identify individuals [20]. A decade ago, studies showed that ECG to be unique for each person and has the potential to be used as a biometric [21]. In this thesis, ECG data were collected in various body positions and during motion, which can impact ECG signal quality. ECG signal quality analysis was performed to reject ECG of poor quality. The signal quality analysis led to the rejection of 193 (57.8%) out of 343 false identifications at the loss of 25 (8.14%) out of 307 true identifications.

1.3 Thesis Outline

The thesis is divided into seven chapters. Chapter 1 introduces the problem, states the objectives, and summarizes the contributions. Chapter 2 provides the background of the concepts used in the thesis and high-level literature review of signal quality analysis and ST segment deviation estimation algorithms. Chapter 3 is the methods detailing the development of the test data, the signal quality gating algorithm, and the equipment and

software utilized. Chapter 4 provides the results and discussion, regarding performance evaluation on the signal quality gating system. Chapter 5 details the development of the ST segment deviation trend estimation algorithm and the integration of the trend estimation algorithm with the previously developed signal quality gating system. Chapter 6 presents the investigation of the application of signal quality analysis in ECG-based biometrics. Chapter 7 presents the conclusions and future work.

2 Chapter: Background and Literature Review

This chapter provides the background on the cardiovascular system, the basics of the electrocardiogram (ECG), and the causes of myocardial ischemia. The chapter also explores the previous work done to mitigate false alarms and provides a high-level literature review of estimation of ST segment deviation.

2.1 Cardiovascular System

The cardiovascular system is responsible for circulating blood throughout the body delivering much-needed nutrients and oxygen [22]. The system is comprised of the heart and the vessels carrying the blood [22]. The heart is the main organ of the cardiovascular system and is responsible for the pumping action [22]. It is divided into four chambers, the right atrium, the left atrium, the right ventricle, and the left ventricle [23]. The right and left atriums are responsible for pumping the blood into the ventricles; the right ventricle is responsible for circulating the blood through the lungs for oxygenation while the left ventricle is the chamber responsible for pumping the blood to the entirety of the body [24].

The pumping action of the heart is initiated by the electrical impulse generated in the Sinoatrial (SA) Node, located on top of the right atrium [23]. As the pumping action progresses, there is an associated electrical activity generated by the heart tissue, known as the ECG (described in Section 2.3).

The heart is mainly composed of muscle tissue called the myocardium [24]. The coronary arteries are the blood vessels supplying the nutrients and oxygen to the myocardium [24].

Any occlusion of the blood vessels can lead to catastrophic complications leading to the death of cardiac tissue and subsequently the death of the patient. Figure 2.1 shows the anatomy of the heart with major structures labeled.

Figure 2.1 Anatomy of the heart with major structures labeled including both ventricles, right atrium and coronary arteries [25].

2.2 Myocardial Ischemia

Ischemia is the reduction of blood supply to tissue leading to a shortage of the oxygen and nutrients required to maintain basic cell functionality [26]. Long-term ischemia will eventually result in the death of the tissue [26]. Myocardial ischemia is the shortage of blood supply to the myocardium tissue reducing the oxygenation of the heart [7]. Myocardial ischemia is associated with and the leading cause of myocardial infarction (i.e., heart attack) [27]. Myocardial infarction is the death of the myocardium tissue [28], [29].

Myocardial infarction is caused by the occlusion of one of the coronary arteries and is considered severe when the occlusion occurs in one of the arteries supplying the left ventricle [28], [29]. Myocardial ischemia can be detected using various techniques, such as an electrocardiogram (ECG) [29]. Once detected, β -Blockers, a class of drugs that reduces the stress on the heart thereby lowering its demand for blood offsetting any decrease in the supply, can be administered in order to prevent the onset of myocardial infarction [5].

2.3 Electrocardiogram (ECG)

Electrocardiogram (ECG) is the recording of the electrical activity in the heart generated prior, during, and after the pumping of the blood [30]. The distinct electrical signature of the heart can be seen in an ECG, which is comprised of five waves (Figure 2.2): P-wave, Q-wave, R-wave, S-wave, and T-wave [30], [31]. These waves are also known as fiducial points as they provide a reference for signal processing algorithms. The P-wave is generated by the contraction of the atria muscles [32]. The QRS waves, which are typically referred to as a QRS complex, are generated by the depolarization of the ventricles [32]. The T-wave is associated with the relaxation, also referred to as repolarization, of the ventricles [32]. The PR segment is also known as isoelectric line and lies between the end of the P-wave and the beginning of the Q-wave [33]. The PR interval is the time interval from the beginning of the P-wave till the beginning of the Q-wave [32]. The ST segment lies between the end of the S-wave, also known as the J point, and the beginning of the T-wave [32]. The QT interval is the time interval from the peak of the Q-wave to the end of the T-wave [33].

Figure 2.2 A typical ECG waveform with PQRST waves and the intervals between the waves labeled [34]

The standard five waves of ECG can be viewed from multiple projections known as leads [11]. These leads can be arranged to provide a complete picture of the electrical activity of the heart. In common clinical practice, there is a total of 12 leads derived from 10 wires connected to the body; Figure 2.3 shows the positioning of wires on the body to obtain the 12 leads.

Figure 2.3 The placement of the 10 wires on the body to record 12 lead ECG [35]

Over the years there have been variations to the 12 lead setup; however, it has been proven to be superior in detecting minute events [11]. The 12 leads are known as Lead I, II, III, V1, V2, V3, V4, V5, V6, aV_R, aV_L, and aV_F [32]. Figure 2.4 shows the leads and the projections they present. Leads V1, V2, V3, V4, V5, and V6 are collectively known as the precordial leads [23].

Figure 2.4 Projections of the ECG leads in the sagittal, frontal and transverse planes of the body [23]

2.3.1 ECG Acquisition

ECG is a representation of an electrical signal generated deep within the body. Therefore, it requires sensitive equipment to measure the electrical signal. A typical ECG acquisition system is comprised of a bio-amplifiers, right-leg driver circuitry, analog filters, protection circuitry, and analog to digital converter (ADC) [36]. A bio-amplifier is comprised of differential amplifiers that have been cascaded to measure small voltage signals, such as

the heart electrical signal, to deter noise, and to have high input impedance [36]. The right-leg driver is a circuit designed to negate noise found in the ECG. Analog filters is an additional step to limit the bandwidth of the ECG to reduce noise and prevent saturation of the ADC during digitization [36]. The protection circuitry decouples the patient from any power source preventing electrocution. The ADC digitizes the signal for transmission to a computer, for storage, and for analysis.

Most of ECG acquisition systems require direct contact with the patient's skin, which is achieved through the use of surface electrodes. There are two types of electrodes: 1) dry (polarizable), and 2) wet (non-polarizable) [36]. Dry electrodes do not require any gel or liquid to conduct the heart's electric current to the ECG acquisition system while wet electrodes require a gel or liquid to conduct the current [36]. In most hospital-based diagnostics systems, wet electrodes are utilized with ECG acquisition systems; silver/silver chloride (Ag/AgCl) electrodes are commonly used.

2.3.2 Ambulatory ECG

Patients are usually advised to ambulate following surgery to promote faster recovery; therefore, the need for a portable ECG acquisition system arises. Postoperative ambulation improves physical function, helps with circulation, and reduces pain, deep vein thrombosis, and urinary tract infection [37]. It also has positive psychological effects on anxiety and symptom distress, and depressive mood [37]. An ambulatory ECG (AECG) acquisition system is similar to an ECG acquisition system with the exception that an onboard memory is included, or a wireless module is integrated with the system. AECG acquisition systems

will record the ECG for off-line analysis by a clinician following the completion of the test or will provide real-time ECG by using an onboard wireless module to transmit the data to a central station where a clinician is available to monitoring the ECG. The gold standard of AECG is the Holter Monitor, which enables long-term recordings (one to two days) that are analyzed offline. The monitor is a small device (about the size of a deck of cards) and can be easily carried by the patient. The Holter monitor detaches the patient from the hospital bed, but the patient movement adds noise to the records increasing the difficulty of the analysis.

2.3.3 Characteristics and Preprocessing of the ECG

The electrical activity of the heart has to travel through the tissue between the heart and the electrode. The tissue inhibits the signal creating an effect called low pass filter effect [36]. The effect reduces the bandwidth of the ECG and the amplitude. The average amplitude of the R-wave is 1 mV while the amplitude of the smallest wave, the P-wave is 0.5 mV [36]. It is worth noting that in a clinical environment ECG signals are typically reported on a graph paper and in millimeters (mm) where 1 mm is equal to 0.1 mV.

In order to mitigate the aforementioned noises, the ECG signal is preprocessed by applying digital filters. The American Heart Association (AHA) recommends applying a zero-phase high-pass filter with a cut-off frequency at 0.67 Hz [38]. Most of the power of an ECG signal lies within the 1 to 40 Hz frequency range; however, some of the diagnostic information can exist beyond that range. Therefore, the AHA recommends applying a low-pass filter with a cut-off frequency at 150 Hz [38].

2.3.4 Noise in AECG

AECG is plagued with environmental and biological noise. Environmental noise includes power line noise and radio frequency noise [36], [39]. Biological noise is generated by the body and is typically in the form of muscle artifacts, baseline wander, and motion artifact [36], [40]. The coupling of the patient and the ECG acquisition system to the electromagnetic waves generated by the power plugs or power line cables leads to power line noise [39]. Baseline wandering is a low-frequency noise produced by the movement of the electrodes over the patient's skin which causes a slow variation in the direct current (DC) component of the skin-electrode interface [36]. Radio frequency noise is generated by wireless communication systems, such as mobile phones, in the MHz and GHz frequency spectrum [39]. Muscle artifact is the noise created by the activation of the skeletal and the smooth muscle fibers, which typically has a higher amplitude than the electrical signal produced by the heart [36]. Motion artifact is caused by patient motion that results in low-frequency noise due to the associated temporally and spatially varying skin potential [41]. Since their source signals are known, and/or they lie outside the AECG frequency range (0.67 Hz – 150 Hz [36]), baseline wandering, radio frequency noise, and muscle artifacts can be mitigated by digital or analog filtering. Analog filtering is typically used to remove noise that would saturate the ADC such as baseline wandering and powerline interference. Digital filtering is used after the ADC to remove noise that wasn't filtered out by the analog filter such as radio frequency noise and muscle artifacts. Even though powerline noise (60 Hz) is within the frequency range of AECG, it can be mitigated by using the right leg driver circuitry and analog notch filters while having minimal effect on the AECG [36]. On the other hand, motion artifact lies within the AECG frequency

range; therefore, attempts to reduce motion artifact can also affect the fidelity of the AECG signal [36]. Motion artifact is of specific interest to this thesis due to the difficulty in removing it from AECG.

2.3.5 Detecting Myocardial Ischemia in AECG

As previously defined, myocardial ischemia is the reduction of the blood supply to the myocardium leading to a decrease in the operation capacity of the myocardium. The myocardium is supplied with blood by various coronary arteries. Therefore, myocardial ischemia is typically localized to specific regions of the myocardium. As the blood supply to the cells is decreased, their electrical conductivity is affected leading to a visible change in the AECG [8]. This effect is most prominent in the ST segment [8].

The ST segment is the region that lies between the end of the S-wave, also known as the J point, and the beginning of the T-wave [42]. The voltage value of the ST segment is measured at 0 milliseconds (ms), 40 ms, 60 ms, 80 ms, 100 ms, and 120 ms from the J point depending on the application [42]. A non-ischemic beat will have an ST segment in line with the isoelectric line of the ECG, the flat region of the signal [33]. An ischemic beat will have an elevated or a depressed ST segment [33]. Figure 2.5 shows a side-by-side comparison of a normal beat and an ischemic beat.

Figure 2.5 a) a normal ST segment, b) an ischemic ST segment. ECG was taken from record 's20011' from Physionet Long-Term ST Database [43], [44]

An ischemic event is the persistence of a deviation of the ST segment from the isoelectric line for a period of time. PROSE declared an ischemic event if the ST segment is elevated from the isoelectric line by at least 0.1 mV for 10 minutes or by at least 0.2 mV for 1 minute [8]. An ischemic event is also declared if the ST segment was depressed from the isoelectric line by at least 0.1 mV for 1 minute [8]. Clinicians typically read the AECG off-line; therefore, ischemic events are declared long after they have occurred losing precious time to intervene. Bedside monitors have introduced automated ST segment analysis algorithms; however, they are typically turned off or ignored by clinicians due to their low fidelity.

It is worth noting that deviations in the ST segment can be caused by non-ischemic beats. Conditions such as left bundle branch block (LBBB) or pericarditis, inflammation of the

heart wall, can also lead to a deviation in the ST segment [45]. Natural variations between humans can also cause deviations in the ST segment. It is normal for healthy adults to have a deviation of 0.2 mV of the ST segment in V2 and V3 [45].

2.4 PeriOperative Ischemic Evaluation (POISE)

Non-cardiac surgeries are a general theme in hospitals with over 100 million adults undergoing non-cardiac surgeries every year [7]. Surgeries place the body under tremendous stress, such as the increase in heart rate, anemia, hypothermia, an increase in free fatty acid concentrations, and an increase in blood pressure which overwork the cardiovascular system [7]. The oxygen demand of the cardiovascular system will increase during high stress to cope with the extra workload; however, any decrease in the blood supply to the cardiac muscles during high stress can lead to catastrophic results, mainly myocardial ischemia [7]. Myocardial ischemia is one of the leading causes of major postoperative cardiovascular complications, such as cardiac death or heart attack which are experienced by over 900,000 patients yearly across the world [7]. These complications also add to the length of stay in a hospital by an average of 7 days, adding more than \$11,000 USD to the hospital costs [4].

Preventive measures, mainly in the form of β -Blockers, can be taken to alleviate the risk of developing a myocardial ischemia. β -Blockers are a class of drugs that mitigate the effects of stress on the cardiovascular system by blocking the receptors of adrenaline, a stress hormone, in the myocardium thereby preventing an overloading the heart [5]. β -Blockers are considered a prophylactic approach and are given to any patient who has

undergone a non-cardiac surgery; however, the effectiveness and side effects of the drugs were not fully investigated [7]. The PeriOperative Ischemic Evaluation (POISE) trial was established to study efficacy and side effects of β -Blockers.

POISE was conducted over the span of five years and recruited over 9000 participants aged 45 or older and expected to undergo a noncardiac surgery with at least one day stay at the hospital following the surgery [7]. Recruited participants also fulfilled one of the following criteria: history of coronary artery disease, peripheral vascular disease, stroke, hospitalization for congestive heart failure within the previous 3 years, undergoing major vascular surgery, or any three of seven risk criteria (undergoing intrathoracic or intraperitoneal surgery, history of congestive heart failure, transient ischemic attack, diabetes, serum creatinine $>175 \mu\text{mol/L}$, age >70 years or undergoing emergent or urgent surgery). Of the recruited participants, 4177 were given a placebo, and 4174 were given a β Blocker [7].

The trial revealed that 152 of the β -Blocker group experienced non-fatal myocardial infarction compared to 215 of the placebo group [7]. On the other hand, 27 of the β Blocker group experienced a stroke compared to 14 of the placebo group [7]. The trial concluded that β -Blockers reduced the risk of postoperative cardiovascular complications. However, they increased the risk of death, stroke, and clinically significant hypotension and bradycardia [7]. The trial's recommendation was the reconsideration of the guidelines recommending β -Blockers to patients undergoing non-cardiac surgery.

At The Ottawa Hospital (TOH), Dr. Homer Yang, an anesthesiologist, was the principal investigator for the POISE study, subsequently established the PeriOperative Ischemia Reduction Studies (PROSE) to move from a prophylactic approach of the usage of β -Blockers to a more targeted approach by only administering β -Blockers to patients at risk [8].

2.5 PeriOperative Ischemia Reduction Studies (PROSE)

The PeriOperative Ischemia Reduction Studies (PROSE) was initiated at The Ottawa Hospital by Dr. Yang to investigate the targeted usage of β -Blockers. PROSE utilized automated ST segment analysis algorithms available in bedside monitors to predict the incidence of myocardial ischemia; a prerequisite of major heart conditions. The bedside monitor considered an ST segment deviation greater than 0.1 mV or less than -0.1 mV to be an ischemic event [8]. When a myocardial ischemia event was detected, the bedside monitor would sound an alarm and send a notification to the clinicians' mobile phones in the form of a pop-up notification that remained on the mobile phones' screens only for 3 minutes [8]. Postoperative patients were requested to ambulate as a routine in their recovery, so the wireless telemetry unit accompanying the bedside monitor was used to collect and monitor the AECG in real-time. Since the bedside monitor generated an alarm every time a deviation in the ST segment was detected, motion artifacts caused hundreds of false alarms increasing the risk of alarm fatigue. TOH developed a white-box solution to mitigate the false alarms.

2.5.1 PROSE White Box Solution

The purpose of the PROSE white box solution is to detect the incidence of ischemic events while mitigating the false alarms. The solution also provided instant notification to clinicians' mobile phones in the form of an email to facilitate a quick intervention which is similar to the functionality offered by the bedside monitor; however, the white box would also provide the previous 20 minutes of ST trend to the clinicians for reference [8]. Figure 2.6 shows the existing system and the PROSE white box solution. The PROSE white box solution used leads II and V5 to detect myocardial ischemia and defined the ST segment level to be 60 ms from the J point [8].

Figure 2.6 Illustration of existing monitoring system employed at TOH and the PROSE white box solution (custom monitoring system) as presented in [8]

To mitigate the effect of noise on the estimations of the ST segment and subsequently the number of false alarms, a baseline value of the ST segment deviations was used to determine the significance of the deviations [8]. The baseline value of the deviations was established as a sliding 1 to 2 minutes window of ST segment measurements based on the run duration of the system [8]. The sliding window mitigated the large values generated by the bedside monitor such as 9 mV which can be biologically infeasible.

Each new measurement was compared to the baseline, and if the value deviated from the baseline, it was counted as deviated segment. If there were consecutive measurements for 10 minutes that exceeded 0.1 mV deviation criteria the white box sounded an alarm [8]. Similarly, if there was 1 minute of consecutive measurements that exceeded the 0.2 mV deviation criteria or the -0.1 mV deviation criterion, the system sounded an alarm [8].

The white box solution greatly decreased the false alarm rates. The solution was tested, and it was found to generate 50 alarms compared to the 146 alarms produced by the bedside monitor over the same test set. The gold-standard, created by the Holter monitor, confirmed that all of the alarms were false.

The system was tested at The Ottawa Hospital (TOH) and during the testing period it actually detected a myocardial ischemia episode in one of the patients and led to saving the patient's life. The patient had a routine surgery and did not exhibit any signs of cardiovascular complications. However, late in the evening, an alarm was sent to the clinician indicating a deviation in the ST segment. The night shift nurse was contacted for an update, and the patient seemed to be okay and sleeping. Upon further look and testing, it was found that the patient was experiencing a myocardial ischemia episode and was bleeding internally. Immediate action was taken, and the patient's life was saved. Even though the solution helped save a patient's life, its false alarm rate was still unacceptable to be deployed at the hospital. A new project was initiated to investigate and integrate AECG signal quality analysis with the white box solution.

2.6 Signal Quality Analysis

Following the development of the white box solution, an investigation into employing signal quality analysis was initiated at Carleton University in conjunction with The Ottawa Hospital. The goal of the project was to develop an algorithm capable of analyzing the quality of the AECG signal and gating the alarm generated by noise contaminated AECG segments.

2.6.1 Signal Quality Analysis Categories

Signal quality analysis has been generally done by technicians overseeing the test or reviewing the data offline following data collection; however, with the rise of automated systems being used and integrated into hospital systems, the automated signal quality analysis is in more need than ever [46]. Manually reviewing the data is prone to human error and is time-consuming.

Signal quality analysis can be divided into four categories: 1) Detection, 2) identification, 3) quantization, and 4) mitigation [46]. *Detection* is the step required to observe the noise or artifacts in the data. *Identification* is recognizing and categorizing the noise and artifacts [46]. *Quantization* is determining a value representative of the amount of noise present in the signal [46]. Quantization can be performed without identification of noise such as using Signal-to-Noise ratio (SNR) [46]. *Mitigation* is the reduction of the severity of the identified noise or artifact through means of the signal processing [46]. Mitigation is typically not warranted in long duration monitoring systems since simply rejecting the noisy segments can be sufficient and not reduce the overall performance of the system [46]. Additionally, applying mitigation techniques to low power noise or inconsequential noise

can have adverse effects on the signal [46]. Quantization of the noise and artifacts in AECG will be the main concern in this thesis.

2.6.2 Current State of Signal Quality Analysis

The notion of signal quality analysis has been around for some time in other fields such as telecommunication and speech analysis where the system is autonomous [47]; however, it is only recently that signal quality analysis has been considered for biosignals [46]. Biosignals are typically reviewed by operators and technicians who can determine the quality of the signal visually and reject any low-quality signals. As more autonomous systems are introduced into the hospital environment and into the daily lives of the average consumer (e.g., heart rate monitors), the need for biomedical signal quality analysis is growing [46]. More research is being conducted in the area of biosignal signal quality with techniques such as the heart rate variability or machine learning to classify the biosignal as clean or noisy being studied [48], [49].

Heart rate is the number times a heart beats in a minute [33]. It is calculated by counting the number of R-waves in a minute or can be obtained instantly by dividing 60 seconds by the time interval between each R-wave, known as RR interval, as shown in (2.1).

$$HR = \frac{60}{RR\ Interval} \quad (2.1)$$

Heart rate variability is the natural change in the heart rate of an individual over time [33]. Low heart variability is an indication of a cardiovascular disease [50]. Conversely, a

significant heart variability can be used as an indication of noise since the R-wave detection algorithms are most likely falsely detecting R-waves [48]. Within the context of signal quality analysis, heart rate variability is considered as a signal quality index (SQI), a qualitative or a quantitative value representing the quality of the biosignal. Other SQIs are the relative power of the QRS complex and the ratio of the number of beats detected by different algorithms [48]. These SQIs can serve as features for a classifier which improves the overall performance of the system. It should be noted that most of the SQIs currently being researched are application specific such as reduction of false alarms during arrhythmia [48], [51].

Following the development of the white box solution at TOH, a project was initiated at Carleton University to develop an algorithm to perform signal quality analysis on AECG data and gate false alarms generated during low signal quality.

2.6.3 Signal to Noise Ratio as SQI

Signal to noise ratio (SNR) is the ratio of the signal of interest to the contamination or artifacts in the signal [52]. Calculation of SNR is shown in (2.2). It is typically presented in decibels (dB); conversion to dB is shown in (2.3).

$$SNR = \frac{P_{Signal}}{P_{Noise}} \quad (2.2)$$

$$SNR_{dB} = 10 \log_{10} \left(\frac{P_{signal}}{P_{Noise}} \right) \quad (2.3)$$

SNR requires knowing the power of the signal and the noise; however, the noise and the signal can be hard to separate, therefore, and estimation of their power is required. In the case of AECG, the signal in question is the PQRST waves described in Section 2.3, and the noise is the environment and biological contaminations outlined in Section 2.3.4. The PQRST waves originate from the action potentials occurring in the heart which are an all or nothing phenomenon, either occur in their entirety or do not occur [36]. This leads to the conclusion that the PQRST waves will usually have the same form. Therefore, ensemble averaging will provide a representative PQRST, assuming uncorrelated noise. Some variations in the PQRST waves may happen due to external factors such as high heart rate during physical activity; however, the changes are negligible when analyzed using short time segments [53]. The power of the signal is considered the power of the representative PQRST [52], [19]. The noise can be estimated by subtracting the representative PQRST from each beat, and the remaining signal is considered the noise present in the beat [52], [19]. Following the subtraction operation, the power of the remaining signal is calculated and is assumed to be the power of the noise. The mean, median, 25th percentile, and minimum of the beats' SNR in a segment were considered as a representative of the signal quality of a segment of an AECG [18], [19]. Testing of the various SNR based SQI has shown a linear relationship between the actual signal's SNR and the SNR based on the estimates of the PQRST and the noise, deeming the SNR as a viable SQI [18], [19], [52]. The 25th percentile SNR estimate have displayed the highest correlation with the actual signal's SNR [18], [19]. The strong correlation between the SNR estimate and the actual signal SNR was regardless of the deviation in the ST segment [18].

2.7 Gating Alarms Using SNR-Based SQI

Following the development of the SQIs based on SNR, the project at Carleton University performed some initial research into a false alarm gating system. The project proposed three techniques to gate the alarms: 1) gating ST values ($SQVS_{ST}$), 2) enabling/disabling Alarm Generation Stage ($SQVS_{EN}$), and 3) Gating generated alarms ($SQVS_{AL}$) [18]. $SQVS_{ST}$ will gate an ST value produced by the bedside monitor during low-quality segments. $SQVS_{EN}$ will toggle the operation of the alarm generation algorithm based on the signal quality. $SQVS_{AL}$ will gate the alarm after they are generated. The second technique was found to have superior results compared to the other two techniques after testing on a small data set, 2 patients, with fixed noise durations [18].

During the initial testing of the three techniques, it was found not all false alarms are generated by noise; false alarms were also generated due to misidentification of fiducial points, such as the J point and the P-wave, by the bedside monitor resulting in an overestimation of the deviation of the ST segment [18].

2.8 Current State of Automated Estimation of ST segment

The measurement of the ST segment deviation requires the identification of the P-wave and the J point also known as fiducial points [33]. To determine these fiducial points, the QRS complex is also needed. Algorithms to identify the QRS complex has been around since the 1980's, such as the Pan-Tomkins algorithm [54]. The Pan-Tomkins algorithm has been successfully used to identify the R-wave and has spawned many variations. Time windows can then be used to determine the locations of the other fiducial points.

Another popular method to estimate the ST segment deviation is the Karhunen-Loève transform (KLT) [55]. KLT provides a set of coefficients that describes the ST segment. The coefficients are utilized to estimate the actual form of the ST segment. The wavelet transform is another type of transform that is used to assess the ST segment. It derives the frequency domain as a function of the time domain which can localize fiducial points, such as the R-wave, where abrupt changes in the signal occur [56]. Bedside monitors typically employ propriety algorithms to estimate the ST segment deviation and thus in-depth analysis of the bedside monitor used by PROSE and SQVSEN was not possible.

The work in this thesis will further explore the notion of using slopes to locate the fiducial points and subsequently estimate the ST segment deviation. It will employ the Pan-Tomkins algorithm and then expand on it to locate the P-wave, the isoelectric line, and the J point.

2.9 Summary

Postoperative myocardial ischemia is a leading cause of the myocardial infarction, heart attack, increasing the morbidity and mortality of the postoperative patients. The incidence of myocardial ischemia had been noted to increase following non-cardiac surgery. The effects of myocardial ischemia are mitigated using β -blockers, a class of drugs responsible for easing the stress on the cardiac tissue by blocking the stress receptors. A randomized controlled trial (POISE) concluded that β -blockers do reduce the incidence of myocardial infarction; however, they also have side effects including bradycardia, hypotension, stroke,

morbidity, and mortality. Therefore, it is recommended to only administer β -blockers to patients at risk.

Myocardial ischemia causes a deviation of the ST segment in an ECG. Automated bedside monitors are available to analyze the ST segment for deviations, but they are plagued with false alarms due to noise contamination which most likely arises from the motion of the patient.

A white box solution was developed at TOH to mitigate the false alarms generated by the bedside monitors. It only generated 50 false alarms compared to 146 false alarms produced by the bedside monitor over the same test signal. Despite the vast improvement, the false alarm rate of the solution is still unacceptable for clinical use. A follow-up project was initiated at Carleton University to gate false alarms based on signal quality analysis of the signal. An SNR based SQI was investigated and was found to be representative of the actual SNR of the signal. A proposed solution using the SNR based SQI ($SQVS_{EN}$) has shown promise on a small data set with fixed noise duration. The work presented in this thesis further developed the proposed solution and tested it on a large dataset. One of the contributions of this thesis is the development and testing of ST segment deviation trend estimator. The ST segment deviation trend estimator algorithm was integrated with the SQI SNR based alarm gating system to gate false alarms due to noise and misidentification of fiducial points.

3 Chapter: Methodology

The three primary objectives of the thesis were: 1) Develop the SQVS_{EN} alarm gating system and evaluate its performance on a large dataset, 2) Develop and integrate an ST segment deviation trend estimator algorithm with SQVS_{EN} alarm gating system, and 3) Investigate the applicability of signal quality analysis in ECG-based biometric systems. The following section details the equipment, test signals, and statistical analysis for the first objective. The second objective was accomplished using the same methodology (test equipment and test signal); however, the in detail description of the ST segment deviation trend estimator algorithm is in Chapter 5. The last objective of the thesis generalized the SNR based SQI to ECG biometrics which required the use of a different test set and test procedures discussed in Chapter 6. Please note that sections of this chapter were adapted from [57].

3.1 Proposed System Overview

The proposed solution to reduce the false alarm rate is a gating system based on signal quality and estimation of ST segment deviation that operates in parallel with the commercial system to gate any alarms generated from a low-quality AECG signal. Figure 3.1 shows a diagram of the proposed system, with the alarm gating components enclosed within the dashed lines. The AECG is collected by a wireless telemetry unit and is transmitted wirelessly to the commercial ECG bedside monitor. The commercial ECG bedside monitor performs analysis of the ST analysis. Simultaneously, the quality of the ECG is being analyzed. The results of the analysis (SQI and trends correlation) are used to

enable and disable the alarm generation algorithm thereby gating false alarms. The server and smartphone stages are part of the solution described in [8].

Figure 3.1 Block diagram of the proposed system showing the route taken by the ECG signal from the wireless ECG transmitter to the commercial bedside monitor where the ST segment is analyzed for deviation. The quality analyzer, encased by the dashed line, is running in parallel to the ST analysis system and disables the alarm generating an algorithm based on a signal quality index (SQI) and the ST trends correlation. The shaded elements were implemented in [8] as an alarm delivery system to clinicians but are not used in this study.

3.2 Data Set

To simulate the AECG data with noise contamination, online data sets from Physionet were retrieved. Physionet is a repository of biosignals data sets and open-source software that was first established in 1999. The data sets used in this thesis were from the Long-Term ST Database (LTSDB) and the MIT-BIH Noise Stress Test Database (NSTDB) available in Physionet.

3.2.1 Long-Term ST Database

ECG recordings from Physionet's Long-Term ST Database (LTSTDB) [44], [43] were used in this thesis. The database contains 86 ECG recordings with ischemic ST deviations collected from 80 human subjects. A total of 68 records contains two leads of ECG data; while the remaining 18 records have three leads [44]. Each of these records is between 20 and 24 hours long. The sampling rate of LTSTDB ECG recordings is 250 Hz with ADC gain of 200 ADC units per mV. PROSE used leads II and V5 to monitor ST deviations [8]. This configuration was not available in LTSTDB; therefore, recordings with leads II and V2 were considered since they were the most similar to the ECG leads considered by PROSE. A total of 16 records with leads II and V2 were found in LTSTDB and used in this study. The manually corrected ST values at J+60ms from the annotation file '16a' were utilized. Table 3.1 lists the 16 ECG recordings and their durations.

Table 3.1 ECG recordings used in the study and their durations

Name	Duration (HH:MM:SS)
s20011	22:52:59
s20051	21:18:44
s20061	22:44:58
s20071	21:05:15
s20081	22:48:49
s20091	22:30:28
s20101	20:22:10
s20111	22:11:16
s20121	21:21:44
s20131	20:55:10
s20141	21:47:43
s20201	20:58:47
s20211	23:08:50
s20221	21:40:32
s20231	23:25:45
s20241	23:22:01

Lead II from s20091 and s20121 and lead V2 from s20081, s20121, s20221, and s20241 were omitted from the analysis since they contained full record alarms.

3.2.2 MIT-BIH Noise Stress Test Database

To simulate motion artifact present in AECG, motion artifact available in the ‘em’ record from Physionet’s MIT-BIH Noise Stress Test Database (NSTDB) was used to contaminate the ECG recordings [58], [43]. The ‘em’ recording is 30 minutes long and has two signals named ‘noise 1’ and ‘noise 2’. The sampling rate of the ‘em’ record is 360 Hz; prior to use, it was downsampled to 250 Hz using the ‘resample’ function in MATLAB to match the sampling rate of the ECG recordings. ‘Noise 1’ was used to contaminate lead II of the ECG signal, and ‘Noise 2’ was used to contaminate lead V2 of the ECG signal.

3.2.3 Synthetic ECG

As shown in Figure 3.1, the testing of the system was performed using a bedside monitor. Synthetic ECG was used as markers to identify the beginning and end of the signals in order to synchronize the ST analysis and ECG signal quality analysis; the synthetic ECG provides a signal with known, repeatable, and distinct characteristics. The synthetic ECG was generated using the ‘ecgsyn’ algorithm available on Physionet [43]. The input parameters of the algorithm are the mean heart rate, the number of beats, sampling frequency, PQRST morphology, the standard deviation of the RR interval, and low and high-frequency contributions. The mean heart rate, number of beats, sampling frequency, and standard deviation of HR were utilized in this thesis while the remaining parameters were left in default (additive noise: 0 mV, low frequency/high frequency ratio: 0.5, order of extrema: PQRST, angles of extrema: [-70 -15 0 15 100], z-position of extrema: [1.2 -5 30 -7.5 0.75], Gaussian width of peaks: [0.25 0.1 0.1 0.1 0.4]). Figure 3.2 shows a sample of the synthetic ECG generated using ecgsyn.

Figure 3.2 Five seconds of synthetic ECG generated using ecgsyn at 90 beats per minute

3.3 Test Apparatus and Software

3.3.1 Bedside Monitor and Wireless Telemetry Unit

The commercial bedside ECG monitoring system employed in this study is manufactured by Spacelabs Medical (Issaquah, WA, USA) and is composed of a wireless telemetry unit (Ultraview Digital Telemetry Multiparameter Transmitter 90345; Figure 3.3), which transmits ECG for analysis to the bedside monitor (91369 Ultraview SL Bedside Monitor; Figure 3.4).

Figure 3.3 91369 Ultraview SL Bedside Monitor manufactured by SpaceLabs

**Figure 3.4 Ultraview Digital Telemetry Multiparameter Transmitter 90345
manufactured by Spacelabs**

The bedside monitor provides an ST segment measurement for each ECG lead every 5 seconds that is based on the average of the past 30 – 60 seconds of ECG signal [59]. The bedside monitor also sends the heart rate (HR) and timestamp at which the HR and ST segment measurements were acquired over a serial port connected to a computer. A custom MATLAB script was used to log the bedside monitor data. Note that the bedside monitor did not provide a log to the computer if HR was not detected. If the bedside monitor detected HR but was unable to compute an ST measurement, it sent an unknown value, ‘?.??’, to the computer. The unknown value was assigned the numerical value ‘10’, which was outside the normal range of ST measurement (between -0.1 mV and 0.1 mV), and was used to modify the operation of the alarm generation procedure as described in Section 3.5.

3.3.2 Patient Simulator

After the construction of the test signals, they were fed to the wireless telemetry unit using the patient simulator (MS400, CONTEC Medical Systems, Qinhuangdao, Hebei Province, P.R. China; Figure 3.5). The patient simulator provided the option of selecting the leads and outputting custom signals which in this thesis were the test signals. The simulator also had the possibility of playing signals from an onboard memory or an SD card.

Figure 3.5 Patient simulator MS400 manufactured by CONTEC Medical Systems

3.4 Signal Quality Index (SQI) Generation

3.4.1 Preprocessing

Prior to generating the SQI, AECG signals were filtered using a high pass zero-phase third order digital Butterworth filter to remove any baseline drift; a 0.67 Hz cut-off frequency was used as recommended by the American Heart Association [60]. The signal quality index (SQI) was generated every 5 seconds based on the previous 30-seconds of AECG data to match the operation of the bedside monitor.

3.4.2 Identification of the R-Wave

The generation of the SQI required the identification and separation of each beat. The R-wave is considered one of the important fiducial points due to its prominence in the PQRST waves and it is typically used to identify the beat. The R-wave was identified using the Complete Pan-Tompkins Implementation ECG QRS detector toolbox available on MATLAB File Exchange [61]. The toolbox is based on the Pan-Tompkins algorithm that was first introduced in the 1980s [54]. The algorithm relies on differentiating and integrating the signal in order to detect the R-wave. It employs a set of variable thresholds to verify the authenticity of the detected wave through discrimination of noise peaks and signal peaks in order to adapt to new signals [61]. Figure 3.6 shows the output of the Pan-Tompkins algorithm where the R-wave is marked, and the variable threshold levels are indicated.

Figure 3.6 Identified R-Wave in a 5-second ECG segment using Pan-Tompkins algorithm. The top graph shows the R-wave on filtered QRS. The middle graph shows the R-wave on the squared signal. The last graph shows the pulse train on the unfiltered ECG signal

3.4.3 Estimation of Signal and Noise Power

The SQI used in this thesis is based on the work in [18], [19], and [51]. To generate the SQI, each beat in a 30-second analysis window was identified by its R-wave. Each beat was isolated into a 0.7-second segment, $W_m[n]$, with the peak of the R-wave centered at 0.35s within the segment. The subscript m identifies the beat number in the 30-second analysis window, and the n identifies the sample number within the beat (e.g., $W_{10}[21]$ refers to the 21st sample of the 10th beat). Partial beats that may exist at the beginning and the end of the 30-second segment were discarded.

3.4.3.1 Ensemble Averaging

Heart beats are based on all-or-nothing action potentials generated in the heart muscle; this suggests that for a given individual, each beat in the analysis window should be identical [23], [36]. Various changes in the beat morphology can occur due to different factors; however, the analysis window is relatively short such that the changes are deemed negligible [53]. Therefore, the ensemble average of the beats in the analysis window can be used to represent the ideal beat for that window, assuming uncorrelated noise. The R-waves of the beats were aligned, and ensemble averaged to produce an estimate of the ideal noise-free beat. The ensemble averaged beat, $W_{avg}[n]$, is described in (3.1).

$$W_{avg}[n] = \frac{1}{M} \sum_{m=1}^M W_m[n] \quad (3.1)$$

where M represents the total number of complete beats in the analysis window. Any deviation from the ideal beat is considered as noise. Figure 3.7 shows an example of ensemble averaging where 90 seconds of ECG were contaminated with white gaussian noise generated using the ‘wgn’ function available in MATLAB.

Figure 3.7 Ensemble averaged 90 seconds of ECG data with added white gaussian noise generated using ‘wgn’ function available in MATLAB. The red line is the ensemble averaged beat.

3.4.4 Calculating Signal to Noise Ratio

The SNR was estimated for each beat. SNR for beat m is described in (3.2), where the numerator is the power of the ideal beat ($W_{avg}[n]$) and the denominator is the noise power (deviation from the ideal beat).

$$SNR_m = 10 \log_{10} \frac{P_{signal}}{P_{noise}} = 10 \log_{10} \frac{\frac{1}{N} \sum_{n=1}^N W_{avg}[n]^2}{\frac{1}{N} \sum_{n=1}^N (W_m[n] - W_{avg}[n])^2} \quad (3.2)$$

where N is the number of samples within a beat. The SQI of the 30-second analysis window was the 25th percentile of all of the SNR values computed from the window. This SQI was shown in previous work to have a good correlation with the SNR of an ECG recording [19].

3.5 Alarm Generation Criteria and Implementation

Alarms were generated based on the PROSE alarm criteria, summarized in Table 3.2.

Table 3.2 Alarm generation criteria

ST Deviation From Isoelectric Line (mV)	Duration
$ST \geq 0.1$	10 minutes
$ST \geq 0.2$	1 minute
$ST \leq -0.1$	1 minute

An alarm was not terminated until the ST deviation fell within ± 0.05 mV. This was to ensure alarms were not prematurely terminated due to random ST fluctuations caused by noise.

The alarm criteria were implemented as a finite state machine (FSM) in MATLAB. The FSM had 6 states illustrated in Fig. 3; a ‘resting’ state, an ‘alarming’ state, a ‘cool down’ state, and 3 ‘warms up’ states corresponding to PROSE alarm criteria. When an ST

deviation measurement exceeded the limits outlined in Table 3.2, then the FSM entered the corresponding 'warm up' state and logged the time stamp. The FSM stayed in the 'warm up' state as long as the incoming ST deviation measurements met the criteria. If an ST deviation measurement returned to the normal range within ± 0.1 mV then the FSM reverted to the 'resting' state; otherwise when the criterion was fulfilled then the FSM entered the 'alarming' state until the incoming ST deviation measurements fell within ± 0.05 mV at which the FSM entered the 'cool down' state. The FSM remained in the 'cool down' state for 30-seconds to ensure the underlying ischemic event was over then entered the 'resting' state. If an ST deviation measurement fell outside the normal range, ± 0.1 mV, while the FSM was in the 'cool down' state, the FSM reverted back to the 'alarming state'. The transitions between the states were controlled by the ST deviation measurements and 4 timers; 'timer 1' is for the 'warm up state 1', 'timer 2' is for the 'warm up state 2', 'timer 3' is for the 'warm up state 3', and 'timer cool down' for the 'cool down' state. The timers were initiated and reset as transitions are made between the states; the timers were compared to the duration criteria in Table 3.2 and the 30-second cool down criterion.

Table 3.3 summarizes the transitions and timers illustrated in Figure 3.8.

Figure 3.8 Finite State Element (FSM) implementation of alarm generation criteria

Table 3.3 Detailed description of the FSM transitions and the timers

Transition	Transition Criteria	Timer 1	Timer 2	Timer 3	Timer Cooldown
1	$-0.1\text{mV} < \text{ST} < 0.1\text{mV}$	Reset	Reset	Reset	-
2a	$0.1\text{mV} \leq \text{ST} < 0.2\text{mV}$	Increment	-	-	-
2b	$0.2\text{mV} \leq \text{ST}$	Increment	Increment	Reset	-
2c	$\text{ST} \leq -0.1\text{mV}$	-	-	Increment	-
3b	$0.1\text{mV} \leq \text{ST} < 0.2\text{mV}$	Increment	Reset	-	-
4a	$\text{ST} \leq -0.1\text{mV}$	-	Reset	Increment	-
5a	$\text{ST} \leq -0.1\text{mV}$	Reset	-	Increment	-
5b	$0.1\text{mV} \leq \text{ST} < 0.2\text{mV}$	Increment	-	Reset	-
6a	Timer 1 = 10 minutes	Reset	-	-	-
6b	Timer 1 = 10 minute or Timer 2 = 1 minutes	Reset	Reset	-	-
6c	Timer 3 = 1 minute	-	-	Reset	-
7a	$-0.05\text{mV} \leq \text{ST} \leq$ 0.05mV	-	-	-	Increment
7b	$-0.1\text{mV} \leq \text{ST} \leq 0.1\text{mV}$	-	-	-	Reset
8	Timer Cooldown = 30-seconds	-	-	-	Reset

3.6 Gold Standard

Gold standard (GS) alarms were generated by passing the ECG records listed in Table 3.1 through the FSM described in Section 3.5. These records are accompanied in the LTSTDB by annotation files titled '16a' [43], [44]. The '16a' files have details of the ST segment deviation for every beat at various points past the J point such as J+0ms, J+20ms, J+40, J+60ms, etc. These files were established by a group of experts from Slovenia, Italy, and the UK [44]. The J+60ms values associated with each beat were used to generate the GS alarms.

3.7 Test Signals Generation

The ECG signals listed in Table 3.1 were retrieved from the LTSTDB along with 'em' signal from the NSTDB. To simulate the motion artifact in AECG, randomly selected segments from the 'em' signal were added to the ECG signal at random intervals. The random 'em' segments were chosen by using MATLAB's random number generator 'rand' to find a starting point in the 'em' file. The durations of the segments were limited to 1, 2, and 4 minutes, which were also selected randomly using MATLAB's 'randi' function, to simulate short ambulation of a patient. The segments were added at random intervals defined by a normal distribution with a mean of 15 minutes and a standard deviation of 5 minutes. The first 10 minutes of the ECG signals were left intact to allow the 91369 Ultraview SL Bedside Monitor algorithms to initially operate on clean segments.

To ensure that the SQIs generated in Section 3.4 were synchronized with the outputs of the bedside monitor, as shown in Figure 3.1, synthetic ECG with known heart rates was

appended at the start of each test signal. Synthetic ECG was generated with a sampling frequency of 250 Hz at heart rates of 90 beats per minute (BPM), 60 BPM, and 30 BPM using the algorithm stated in Section 3.2.3, a realistic ECG synthesizer provided by Physionet. The generated ECG was amplified digitally by 200 units per mV to match LTSTDB and had a length of 5 minutes: 60 seconds of 0 BPM, 60 seconds of 90 BPM, 30-seconds of 0 BPM, 60 seconds of 60 BPM, 30-seconds of 0 BPM and 60 seconds of 30 BPM. To denote the end of the test signal, 30-seconds of 0 BPM were appended at the end of the signal.

The MS400 patient simulator requires data to be sampled at 100 Hz, 300 Hz, 500 Hz, or 1000 Hz. Therefore the test signals were upsampled to 300 Hz using MATLAB's 'resample' function which was the closest option to LTSTDB sampling rate. The upsampled test signals were converted to the MS400 patient simulator's proprietary file format using CONTEC's Case Conversion software.

3.7.1 CONTEC's Case Conversion software

The CONTEC's Case Conversion software converts the supplied signals to the proprietary file format based on a set of eight parameters set within the software. The parameters are Format, Sampling Frequency, Data Type, Baseline, Data Precision, Calibration, and Leads. The format dictates how each byte should be interpreted. Physionet used data format 16 such that each sample was stored as 2 bytes in two's complements format. The sampling frequency dictated the sampling rate of the data. There are 3 options for the Data Type parameter: 1) char, 2) short, and 3) int. The Physionet data were stored as short. The

baseline was the starting point of the ADC and in Physionet's case; it was 0. Data precision referred to the ADC precision, and Physionet's LTSTDB used 12 bits. The Calibration parameter referred to the ADC calibration, and Physionet's LTSTDB used 200. Leads referred to the number and type of ECG leads that were present in the signal. Leads II and V2 were used. Figure 3.9 show the GUI of CONTEC's Case Conversion and the aforementioned parameters.

The figure displays two windows from the CONTEC Case Conversion GUI. The top window is the main interface, featuring a 'Type' section with radio buttons for ECG (selected), Resp, and IBP. It includes a 'Format' section with radio buttons for 16 (selected) and 212, and a 'Language' dropdown set to English. On the right are 'Convert' and 'Remark' buttons. Below these is a 'List' section with a 'File' list box and buttons for Add, Delete, Up, Down, Order, Clear, and Parameter. At the bottom is a 'Path Setting' section with a text field and a 'Browse...' button. The bottom window is the 'Info Required' dialog. It contains 'Samp Freq' (300 Hz), 'Data Type' (Short), 'Baseline' (0), and 'Data Prec' (12 bits). A 'Case Remark' text area is on the right. A 'Case Info from File' button is also present. The 'ECG' section has a 'Calibration' field (200) and checkboxes for leads I, II (checked), III, aVR, aVL, aVF, V1, V2 (checked), V3, V4, V5, and V6, along with a 'Select All' option. The 'IBP' section has checkboxes for IBP1 and IBP2, each with a 'Calibration' field and a '/mmHg' unit label. The 'Resp' section has a 'Calibration' field and a '/ohm' unit label. 'OK' and 'Cancel' buttons are at the bottom.

Figure 3.9 CONTEC's Case Conversion GUI with parameters setup for test signals

3.8 Test Procedure

The test signals were then individually loaded onto an SD card and then run through the patient simulator to the wireless telemetry unit. The telemetry unit relayed the signals to the bedside monitor where the ST analysis was done, and the results were relayed to the computer. The 91369 Ultraview SL Bedside Monitor has learning functionality which switches the monitor into learning mode to improve the ST estimates. The learning functionality was evoked for each test signal with noise added after the synthetic ECG has been run. In addition to test signals, unaltered signals retrieved from the LTSTDB were run through the monitor after the addition of the simulated ECG sequences described above at the beginning and the end of the signal. The unaltered signals were used to provide baseline performance of the monitor.

3.8.1 Aligning Logged Timestamps and Physionet

It was discovered that after running the test signals through the patient simulator and the bedside monitor that the time stamps of the ST measurements were out of alignment. The results of an investigation suggested that the oscillator of the patient simulator was not operating as expected. The patient simulator ran the test signals at a different frequency than instructed. As an example, the patient simulator ran the signals at 301 Hz instead of 300 Hz which was the test signals were upsampled to. The ECG signal was not affected in the short term, and the morphology was the same; however, over the entire length (~ 24 hours) of a test signal, the misalignment between the logged timestamps and Physionet was over 10 minutes.

To rectify the timestamp misalignment, the bedside monitor time stamps were multiplied by a scaling factor as shown in (3.3).

$$\mathbf{Factor} = \frac{\mathbf{Last\ Physionet\ Sample\ (seconds)}}{\mathbf{Last\ Logged\ Bedside\ Sample\ (seconds)}} \quad (3.3)$$

3.9 Analysis

Precision, also known as Positive Predictive Value (PPV), and Recall, also known as sensitivity, were used in this study to quantify the effectiveness of the alarm gating system. Precision is the percentage of true alarms when compared against all identified alarms. The recall is the ability of a test to classify alarms as true [62]. Precision and Recall are defined in (3.4) and (3.5), respectively.

$$\mathbf{Precision} = \frac{\mathbf{True\ Positive}}{\mathbf{True\ Positive + False\ Positive}} \quad (3.4)$$

$$\mathbf{Recall} = \frac{\mathbf{True\ Positive}}{\mathbf{True\ Positive + False\ Negative}} \quad (3.5)$$

For the purposes of the study, a true positive (TP) was defined as the detection of a GS alarm by an alarm generated from the bedside monitor measurements. Multiple alarms produced by the bedside monitor can occur within a single GS alarm and were counted as a single TP. Multiple GS alarms detected by a single bedside monitor alarm were considered as multiple TPs.

A false positive (FP) was defined as an alarm generated by the bedside monitor measurements when no GS alarm exists. A false negative (FN) was defined as no alarm produced by the bedside monitor measurements when a GS alarm exists. A true negative (TN) was defined as the absence of a previously detected FP. Figure 3.10 illustrates the definitions of TP, FP, and FN.

Figure 3.10 definitions of TP, FP, and FN in the context of this study

4 Chapter: Development and Testing of SQVS_{EN}

Motion artifact is hard to filter using conventional methods since it overlaps the frequency band of the AECG. The added noise has been shown to lead to false alarms in myocardial ischemia monitoring systems rendering them impractical [52]. SQVS_{EN} was proposed in [18] as an alarm gating system based on SNR SQIs. The solution enabled/disabled the alarm generation FSM, described in Section 3.5, based on the SQI of the current AECG segment. Some initial investigation was performed using two ECG signals, s20051, and s20111, from Physionet LTSTDB [18]. The ECG signals were contaminated by 5 minutes noise segments from NSTDB every 15 minutes. The initial results were promising with the system attaining a precision of 1 and a recall of 0.85, though limited due to the small size of the test set and the regular noise pattern. In this thesis, the SQVS_{EN} solution was fully developed and in this chapter, an overview of the system testing, results, and discussion of the SQVS_{EN} are presented. Please note that sections of this chapter were adapted from [57].

4.1 System Overview

SQVS_{EN} enabled and disabled the alarm generation FSM based on the SQI of the AECG segment. The SQI was generated based on the 25th percentile of the SNR of the 30-second window of AECG data. The 30-second window matched the operation of the bedside monitor used to monitor AECG for signs of myocardial ischemia.

4.1.1 Modifications to Alarm Generation FSM

The alarm generation FSM was based on the ST segment deviation measurements and a set of timers. The measurements and the timers were used to switch between the states and determine when an alarm started and ended. The ST segment deviation measurements were governed by the criteria described in Table 3.2 and Section 3.5. With no alarm gating, the FSM was not controlled by the SQI and operated regardless of the quality of the ECG signal. The SQVSEN solution enabled and disabled the FSM based on the SQI; therefore, a condition was added to the FSM to prevent any transitions and to halt the timers in the case of an SQI below the set threshold. If the SQI was below the set threshold, then SQVSEN retrieved the next ST segment deviation measurement and checked if the SQI was still below the threshold. The FSM shown in Figure 3.8 was modified to only transition when the SQI was above a set threshold. Table 4.1 shows the modified FSM transitions with the SQI condition to enable/disable the FSM during AECG segments with low signal quality.

Table 4.1 Detailed description of the FSM transitions and the timers with the addition of the SQI condition which enabled/disabled the FSM

Transition	Transition Criteria	Timer 1	Timer 2	Timer 3	Timer Cooldown
1	$-0.1\text{mV} < \text{ST} < 0.1\text{mV}$ and $(\text{SQI} \geq \text{Threshold})$	Reset	Reset	Reset	-
2a	$0.1\text{mV} \leq \text{ST} < 0.2\text{mV}$ and $(\text{SQI} \geq \text{Threshold})$	Increment	-	-	-
2b	$0.2\text{mV} \leq \text{ST}$ and $(\text{SQI} \geq \text{Threshold})$	Increment	Increment	Reset	-
2c	$\text{ST} \leq -0.1\text{mV}$ and $(\text{SQI} \geq \text{Threshold})$	-	-	Increment	-
3b	$0.1\text{mV} \leq \text{ST} < 0.2\text{mV}$ and $(\text{SQI} \geq \text{Threshold})$	Increment	Reset	-	-
4a	$\text{ST} \leq -0.1\text{mV}$ and $(\text{SQI} \geq \text{Threshold})$	-	Reset	Increment	-
5a	$\text{ST} \leq -0.1\text{mV}$ and $(\text{SQI} \geq \text{Threshold})$	Reset	-	Increment	-
5b	$0.1\text{mV} \leq \text{ST} < 0.2\text{mV}$ and $(\text{SQI} \geq \text{Threshold})$	Increment	-	Reset	-
6a	Timer 1 = 10 minutes and $(\text{SQI} \geq \text{Threshold})$	Reset	-	-	-

6b	Timer 1 = 10 minute or Timer 2 = 1 minutes and (SQI $\geq$ Threshold)	Reset	Reset	-	-
6c	Timer 3 = 1 minute and (SQI $\geq$ Threshold)	-	-	Reset	-
7a	-0.05mV $\leq$ ST $\leq$ 0.05mV and (SQI $\geq$ Threshold)	-	-	-	Increment
7b	-0.1mV $\leq$ ST $\leq$ 0.1mV and (SQI $\geq$ Threshold)	-	-	-	Reset
8	Timer Cooldown = 30-seconds and (SQI $\geq$ Threshold)	-	-	-	Reset

4.2 System Performance

4.2.1 Bedside Monitor Baseline Performance

The baseline performance of the bedside monitor was determined by running the unaltered signals, listed in Table 3.1, retrieved from LTSTDB which accounted for 688 hours of test signals. Synthetic ECG was appended to the beginning and ending of the signals for timing purposes as described in Section 3.7. The signals were run through the bedside monitor individually. Once all of the ST segment deviation measurements were logged from the monitor, the measurements of the synthetic ECG were discarded and the logged time was

aligned with the LTSTDB time as described in Section 3.8.1. Unknown values logged from the monitor were assigned the numerical value ‘10’ and were not considered when generating alarms. The logged bedside monitor deviations were fed to the unaltered FSM described in Section 3.5 and were compared to the gold standard alarms generated from the signals from the LTSTDB ‘16a’ files.

4.2.1.1 Results

There were 99 gold standard alarms found in the 16 signals listed in Table 3.1. Running the unaltered signals through the monitor resulted in 78 TPs, 21 FNs, and 66 FPs. The precision and recall were 0.54 and 0.79, respectively.

4.2.2 SQV_{SEN} Performance

The performance of the SQV_{SEN} was tested using the LTSTDB signals listed in Table 3.1 with added noise. The noise was added randomly according to the procedure described in Section 3.7. Following the contamination of the signals, the SQIs were generated using the procedure describe in Section 3.4. Synthetic ECG was appended at the beginning and ending of the signals for timing purposes. The test signals were processed individually on the bedside monitor, and the ST segment deviation measurements were logged. The measurements of the synthetic ECG were discarded, and the unknown values were assigned the numerical value ‘10’ and were not considered when generating alarms. The alarms were generated using the altered FSM. The thresholds for the FSM were selected to be from -20 dB to 25 dB, where -20 dB represented the case of no gating due to the low threshold and

25 dB represented the extreme gating case. The results were analyzed using the statistics described in Section 3.9.

4.2.2.1 Results and Discussion

Table 4.2 shows the comparison of the TPs, FNs, FPs, and TNs detected in the unaltered signals and in the test signals with no gating applied. Table 4.3 shows the comparison of the TPs, FNs, FPs, and TNs detected in the test signals with no gating and in the test signals with gating at 6 dB threshold. Table 4.4 shows the comparison of the TPs, FNs, FPs, and TNs detected in the unaltered signals and in the test signals with gating applied at 6 dB threshold.

Table 4.2 Comparing the TPs, FNs, FPs, and TNs detected in the unaltered signals and the test signals with no gating applied

	Test Signals With No Gating Applied				
		TP	FN	FP	TN
Unaltered Signals	TP	77	1	N/A	N/A
	FN	0	21	N/A	N/A
	FP	N/A	N/A	54	12
	TN	N/A	N/A	117	N/A

The baseline performance of the bedside monitor system was determined by using the unaltered signals compared to the GS alarms. The baseline performance is 78 TPs, 21 FNs, and 66 FPs, which is reflected in the rows of Table 4.2.

Table 4.2 also shows the effect of noise, which increased the number of FPs to 171. The noise also caused the loss of a TP in the s20061 lead II signal. This was due to noise occurring at the onset of the alarm, which caused the bedside monitor ST estimates to fluctuate and then produce unknown values due to low signal quality. The bedside monitor was unable to recover and detect the TP. Of the 66 FPs associated with the unaltered signals, only 54 FPs were detected in the test signals. The 12 undetected FPs were considered as TNs in the test signals. The loss of these 12 FPs was attributed to the addition of the noise and the inconsistency of the measurements performed by the bedside monitor, which prevented these false alarms from occurring.

Table 4.3 Comparing the TPs, FNs, FPs, and TNs detected in the test signals and the test signals with gating applied at 6 dB

	Test Signals With Gating Applied at 6 dB				
		TP	FN	FP	TN
Test Signals	TP	76	1	N/A	N/A
	FN	0	22	N/A	N/A
	FP	N/A	N/A	54	117
	TN	N/A	N/A	0	12

Table 4.3 shows the effect of gating on the test signals. Gating at a threshold of 6 dB was chosen since it lies in a flat region of TP count while maximizing the gating of FPs, as shown in Figure 4.1. Gating decreased the FPs, with only 54 FPs compared to 171 FPs detected in the no gating case. The proposed solution successfully gated 100% of the noise caused FPs. Gating also led to the loss of a single TP, bringing the total of detected TPs

down to 76 from 77 TPs that were detected in the no gating case. The lost TP was investigated. The noise during this period caused the bedside monitor to overestimate the deviation of the ST segment, which led to a short one minute alarm. The alarm occurred during a GS alarm and therefore was considered as a TP; in other words, the noise helped maintain the TP by chance. At 6 dB, the alarm was correctly gated because of the presence of noise.

Table 4.4 Comparing the TPs, FNs, FPs, and TNs detected in the unaltered signals and the test signals with gating applied at 6 dB

		Test Signals With Gating Applied at 6 dB			
		TP	FN	FP	TN
Unaltered Signals	TP	76	2	N/A	N/A
	FN	0	21	N/A	N/A
	FP	N/A	N/A	54	12
	TN	N/A	N/A	0	N/A

The results presented in Table 4.4 provide a broader view of the effect of gating. The counts of TPs, FN, FPs, and TNs, detected after gating at 6 dB were compared to the counts detected in the unaltered signals. As previously noted, two TPs were lost due to noise. The 54 remaining FPs were studied and found to be generated during clean segments; these segments had high SQIs and were visually confirmed to be noise free. The remaining 54 FPs and the 66 FPs detected in the unaltered signal were further investigated, and the results are presented in Section 4.3.

Figure 4.1 is the visual representation of the changes in the count of TP, FP, and FN detected in the test signals as the SQI threshold level governing the FSM was changed. Additionally, the count of FPs detected in the unaltered signals represented by a solid line is shown for reference. At a low SQI threshold level, the gating of false alarms was minimum since the FSM was enabled during regions contaminated with motion artifacts. The TP and FN were preserved. As the SQI threshold increased, FPs were gated and at extremely high SQI thresholds, FPs were gated at the expense of a decrease in TPs and increase in FNs. At an SQI threshold level of 6 dB, the alarm gating solution eliminated 117 out of 171 FPs while missing 1 TP.

Using the data presented in Figure 4.1, Precision and Recall of the alarm gating algorithm were calculated. Figure 4.2 shows the Precision-Recall Curve (PRC). The recall obtained by the bedside monitor system on the test signals with no alarm gating was 0.78 with a precision of 0.31. The highest precision achieved by the proposed solution that does not affect the initial solution's recall is 0.51.

**Figure 4.1 TP, FP, and FN of all leads of all test signals vs. SQI threshold levels and
FP count in unaltered signals**

**Figure 4.2 Precision Recall Curve showing Precision and Recall of the SQVSEN
alarm gating solution**

In Figure 4.1, the ungated case is represented by SQI threshold level of -20 dB, where the low threshold level ensured that no alarms are being gated. At the ungated case, the solution had a precision of 0.31 and a Recall of 0.78, as shown in Figure 4.2. As the SQI threshold was increased from -20 dB to -3 dB, the proposed system increasingly gated more FP alarms while maintaining the TP's count. The maximum attained precision without compromising recall is 0.51 at 1 dB threshold, which was a 0.20 improvement over the ungated case. This represented the removal of 93% of the FP alarms caused by added noise and 57% of the total FP's count while maintaining the TP's count. Beyond this threshold, the proposed solution's recall was reduced in favor of precision. In this study, by sacrificing one TP, the solution gated 100% of the noise caused FPs and 68% of the total FP's count, achieving an overall precision of 0.58 and recall of 0.77.

It can be noted that the TP count has fluctuated before steadily decreasing starting at 14 dB. Between -9 dB and -3 dB, a TP was lost. In s20081 lead II signal, a TP was generated by the added noise skewing the ST values outside of the normal range. This was a case where noise has resulted in the discovery of a TP. As the threshold level increased, the alarm was correctly gated which led to the loss of the TP. Between thresholds 2 dB and 3 dB, three TPs are lost in the signals s20071 lead V2, s20101 lead II, and s20241 lead II. These alarms were gated due to low SQI preceding the alarm. In few cases, TP alarms were gained due to the low SQI regions not being considered, and the alarm conditions are met. Beyond the 8 dB threshold, TPs start to decrease with the exception of the gain of a single TP at 13 dB. At 13 dB, a low SQI region in s20101 lead II was ignored which extended a

bedside monitor alarm to cover a previously FN. TPs decreased steadily starting at 14 dB where 34 FPs existed.

4.3 Investigation of Misidentification of Fiducial Points

Measuring of the ST segment deviation requires the identification of the J point and the isoelectric line in the AECG signal. These points are known as fiducial points since they are distinct markers in the signal. Misidentification of these fiducial points can lead to overestimation of the deviation of the ST segment. The 54 FPs remaining following the gating at 6 dB and the 66 FPs detected in the unaltered signals were generated during clean ECG segments with high SQI. The FPs were further investigated, and it was noted that the bedside monitor had overestimated the ST segment deviation. The ST segments deviation measurements were within alarm conditions even though the GS measurements were within normal bounds (-0.1 mV to 0.1 mV, exclusive). Figure 4.3 shows an example of the bedside monitor overestimating the deviation of the ST segment; the GS was within normal bounds while the bedside monitor measurements were below -0.1 mV which generated an alarm condition. Figure 4.4 shows an ECG sample from middle of the segment displayed in Figure 4.3; the ECG is clean and does not exhibit any signs noise contamination nor morphological irregularities

Figure 4.3 ST segment deviation overestimation by bedside monitor (red) compared to GS (blue) taken from lead V2 of the record s20051. Alarm conditions are marked as solid black horizontal lines.

Figure 4.4 ECG sample from s20051 during the bedside monitor overestimation of ST segment deviation (please note that this is lead V2; therefore, the R-wave is pointing downwards)

The algorithm used by the bedside monitor is proprietary and could not be accessed. The monitor, however, provided some user control over the location of the measurements. As shown in Figure 4.5, the user is given the control over the site of the isoelectric line (PR segment), J point, and ST segment. These user controls suggest that the algorithm used by the monitor is time-based.

Figure 4.5 ST segment deviation measurement location user interface of Spacelab's bedside monitor.

In addition to providing user controls, the bedside monitor also provided a history of the deviation measurements and provided a visual of the beat where deviation was measured. Figure 4.6 shows an example of the measurements history provided by the monitor where the minimum, maximum, and the last reported events are displayed. In the minimum measurement, it can be noted that the location of the isoelectric line fell on the QRS complex. In the maximum measurement, the ST segment location fell on the T-wave and

similar observation can be made for the last event recorded. The deviation measurements are clearly overestimated which led to false alarms.

Figure 4.6 Deviation measurements history as provided by the bedside monitor

4.4 Summary

Motion artifacts can lead to false alarms in myocardial ischemia monitoring systems reducing their fidelity and rendering them impractical. A solution, $SQVS_{EN}$, was previously proposed to reduce motion artifact induced false using a signal quality index (SQI) based on the SNR of the AECG. Motion artifacts can be noted during low SQI regions of AECG data. The $SQVS_{EN}$ solution enabled and disabled the alarm generation FSM if the SQI of the AECG drops below a set threshold.

The system was tested using contaminated 16 signals from the LTSTDB amounting to 688 hours of test data. Clean signals were used to determine the baseline operation of the bedside monitor which generated 78 TPs, 21 FNs, and 66 FPs attaining precision and recall of 0.54 and 0.79, respectively. The bedside monitor generated 77 TPs, 22 FNs, and 171 FPs on the contaminated signals attaining precision and recall of 0.31 and 0.78, respectively. The $SQVS_{EN}$ solution was applied to the contaminated signals gating 117 FPs

while losing only one TP at 6 dB threshold. The solution attained precision and recall of 0.58 and 0.77, respectively, which was a 0.27 improvement in precision over the bedside monitor performance (precision: 0.31) on the contaminated signal.

A total of 54 FPs were remaining after gating at 6 dB threshold. The FPs were studied and were found to be generated during high SQI AECG regions suggesting that they were not caused by motion artifacts. The bedside monitor was found to misidentify fiducial points in the AECG which caused an overestimation of the ST segment deviation. The overestimation of the deviation led to false alarms.

5 Chapter: Gating False Alarms Generated by Misidentified Fiducial Points

The bedside monitor misidentified fiducial points in the AECG signal leading to overestimation of the ST segment deviation which has caused false alarms as discussed in Section 4.3. An ST segment deviation trend estimation algorithm was developed to work in tandem with the bedside monitor estimations in order to verify the general trend of the ST segment deviation. The algorithm was tested against the 16 clean LTSTDB recordings listed in Table 3.1. In this chapter the development, testing and integration of the trend estimation algorithm with the SQVS_{EN} solution are presented.

5.1 Development of ST segment Deviation Trend Estimation Algorithm

The measurement of the ST segment deviation required the identification of the ST segment and the isoelectric line. In this thesis, the ST segment was defined as the region between the end of the S-wave and the beginning of the T-wave; the isoelectric line was defined as the flat region between the end of the P-wave and the beginning of the Q-wave. As suggested by Figure 4.5 and Figure 4.6, the bedside monitor uses similar definitions of the ST segment and the isoelectric line.

5.1.1 Identification of the R-Wave, Q-Wave, and S-Wave

The R-wave was considered as the most prominent feature in the AECG signal due to its high amplitude compared to the other waves. The R-wave was identified using the Pan-Tompkins algorithm [54]. The Complete Pan Tompkins Implementation ECG QRS detector toolbox available on MATLAB File Exchange was used as the implementation of

the Pan-Tompkins algorithm [61]. Please refer to Section 0 for a description of the algorithm and a sample of the output of the toolbox.

The Q-wave was defined as the inflection point preceding the R-wave, and the S-wave was defined as the inflection point following the R-wave [31]. The QRS complex has an average duration of 0.10 seconds and is centered on the R-wave [31]. Two 0.05 seconds search windows were placed before and after the R-wave to search for the Q-wave and the S-wave. The sample that marked the first inflection point preceding the R-wave was labeled as the Q-wave, and the sample that marked the first inflection point following the R-wave was labeled as the S-wave. If inflection points were not found, the sample marking the beginning of a flat region, a region with a 0.01 mV difference between neighboring samples, was marked as the wave in question. Figure 5.1 shows a sample beat with the search window as the hatched area, and the Q-wave and S-wave highlighted in red.

Figure 5.1 A sample beat from LTSTDB record 's20071' where the Q and S waves are highlighted in red, and the search window is marked by the hatched region.

5.1.2 Identification of the ST segment

The ST segment was defined to be the segment from the end of the S-wave and the beginning of the T-wave. The end of the S-wave is also known as the J point, and it was defined to be the junction where the S-wave met the baseline [42]. The bedside monitor measured the amplitude of the ST segment 0.06 seconds from the J point. The average duration of the QT interval, defined as the peak of Q-wave till the end of T-wave, was defined to be 0.44 seconds [33]. The average durations of the T-wave and the QRS complex were defined to be 0.268 and 0.1 seconds, respectively [33]. The average duration of the ST segment was found by subtracting the average length of the T-wave and the QRS complex from the average QT interval which equaled 0.072 seconds. A search window was established starting at the S-wave and extending for 0.072 seconds toward the T-wave. Within the search window, the sample marking the first inflection point was labeled as the J point. If an inflection point was not found, the sample marking the beginning of a flat region, a region with a 0.01 mV difference between neighboring samples, was labeled as the J point. The J point was crosschecked against the beginning of the T-wave, located by searching for 0.134 seconds of samples with constant slope direction. If the J point was deemed to be within the T-wave, the amplitude of the ST segment was measured 0.06 seconds from the S-wave. Figure 5.2 shows the ST segment highlighted with red in a sample beat, the J point marked with a black dot, and the search window as the hatched region.

Figure 5.2 A sample beat from LTSTDB record 's20071' where the ST segment is highlighted in red, the J point is marked by the black dot, and the search window is marked by the hatched region.

5.1.3 Identification of the Isoelectric Line

The isoelectric line, also known as the PR segment, was defined as the segment between the end of the P-wave and the beginning of the Q-wave [33]. The average durations of the PR interval and the P-wave were defined to be 0.2 and 0.1 seconds, respectively [33]. The duration of the isoelectric line was determined to be 0.1 seconds by subtracting the P-wave duration from the PR interval duration. A 0.1 seconds search window was established at the beginning of the Q-wave and extending backward. The end of the P-wave was located by searching for the 0.05 seconds with consistent slope direction in the search window. The sample denoting the end of the P-wave was labeled as the beginning of the isoelectric line. The last sample donating a flat region, a region with a 0.01 mV difference between

neighboring samples, in the search window was labeled as the end of the isoelectric line. If neither the end of the P-wave nor a flat region were located then beginning of the isoelectric line was labeled to be 0.05 seconds from the Q-wave and the ending of the isoelectric line was labeled to be the Q-wave. If the end of the P-wave was located, however, the flat region was not located then the beginning of the isoelectric line was labeled to be the end of the P-wave, and the end of the isoelectric line was labeled to be 0.05 seconds from the P-wave. If the end of the P-wave was not located and the flat region was located, then the beginning of the isoelectric line was labeled to be 0.05 seconds from the sample denoting the flat region and the end of the isoelectric line to be the sample denoting the flat region. The amplitude of the isoelectric line was defined as the average of the samples labeled as the isoelectric line.

Figure 5.3 A sample beat from LTSTDB record 's20071' where the isoelectric line is highlighted in red, and the search window is marked by the hatched region.

5.1.4 Estimating ST Segment Trend

The amplitude of the ST segment was measured at 0.06 seconds from the J point, and the amplitude of the isoelectric line was estimated as the average of the amplitudes of the samples within the region identified as the isoelectric line. The deviation of each ST segment was estimated by subtracting the amplitude of the isoelectric line from the amplitude of the ST segment. To conform to the operation of the bedside monitor, the ST segment deviation measurements were averaged over 30-seconds window. The window was shifted by five seconds such that the first window was from 0 seconds mark to 30 seconds mark, and the next window was from 5 seconds mark to 35 seconds mark.

The GS was considered to be the '16a' annotation files that accompanied the LTSTDB records listed in Table 3.1. The averaged deviation measurements were multiplied by a scaling factor of 3.89 to minimize the mean square error (MSE) between the '16a' annotations and the averaged measurements. The factor was obtained by averaging the scaling factors that minimized the MSE for each LTSTDB record. Figure 5.4 shows the estimated ST segment deviation trend of the record 's20071' compared to the GS retrieved from LTSTDB. It can be noted that the estimated trend closely followed the GS.

Figure 5.4 Estimated trend of ST segment deviations for LTSTDB record 's20071' (black) compared to GS (blue)

5.1.5 Performance of ST Segment Trend Estimator

The ST segment trend estimator was tested against the GS, '16a' annotations retrieved from LTSTDB for records listed in Table 3.1. The estimated trend and the GS were divided into 10-minute segments offset by five seconds. The duration of the segments was chosen based on the longest time alarm criterion listed in Table 3.2. The GS was downsampled such that there was a measurement every five seconds which mimicked the measurements reporting rate of the trend estimator. The Pearson correlation coefficient, shown in (5.1), was found for every 10-minute segment.

$$r = \frac{\sum X * Y - \frac{\sum X * \sum Y}{n}}{\sqrt{\left((\sum X^2) - \frac{(\sum X)^2}{n} \right) * \left((\sum Y^2) - \frac{(\sum Y)^2}{n} \right)}} \quad (5.1)$$

where r is the unitless Pearson correlation coefficient, X and Y are the samples from the 10-minute segments from the two signals being correlated, and the n is the number of samples in the 10-minute segment. The process was performed on leads II and V2 for the 16 records listed in Table 3.1. For comparison purposes, the process was repeated for the deviation measurements logged from the bedside monitor. Figure 5.5 shows box plot of Pearson correlation coefficient per LTSTDB record of the trend estimator and bedside monitor with the GS for lead II; while Figure 5.6 shows the boxplot of coefficients for lead V2.

Figure 5.5 Pearson correlation coefficient of lead II per record for trend estimator (black) and bedside monitor (red) with the GS.

Figure 5.6 Pearson correlation coefficient of lead V2 per record for trend estimator (black) and bedside monitor (red) with the GS. The error bars represent one standard deviation.

As evident in Figure 5.5 and Figure 5.6, the trend estimator had a higher correlation with the GS than the logged measurements from the bedside monitor with the exception of the lead II of record s20111 and lead V2 of record s20101 where the median of the correlation coefficient of the bedside monitor was better than the trend estimator by 0.03. The average median of r for lead II was 0.57 for the trend estimator and 0.41 for the bedside monitor; while, the average for lead V2 was 0.52 for the trend estimator and 0.37 for the bedside monitor. The trend estimator has generally captured the trend of the ST segment deviation in the GS. Figure 5.7 compares the trend estimator measurements, the logged bedside monitor measurements, and GS for the LTSTDB record ‘s20071’. It can be noted that the

logged bedside monitor measurements were erratic and did not follow the trend of the GS on various occasions.

Figure 5.7 Comparison of the trend estimator measurements (black), bedside monitor measurements (red), and GS (blue) of the LTSTDB record 's20071'

5.2 Gating False Alarms in Unaltered LTSTDB Records

The ST segment deviation trend of both leads of the 16 records listed in Table 3.1 was estimated. The estimated trend was divided into 10-minute segments offset by 5 five seconds. Each 10-minute trend segment was correlated with its respective 10 minute logged bedside monitor measurements segment. Pearson, Kendall, and Spearman correlation coefficients were calculated between each 10-minute estimated trend segment and its respective 10-minute segment of logged bedside monitor measurements. Pearson correlation coefficient was calculated using (5.1), Kendall rank correlation was calculated using (5.2), and Spearman rank correlation was calculated using (5.3).

$$\tau = \frac{n_c - n_d}{\frac{1}{2}n(n-1)} \quad (5.2)$$

where τ is the unitless Kendall rank correlation, n_c is the number of concordant, n_d is the number of discordant, and n is the number of samples in a 10-minute segment. Concordant is the number of samples ordered in the same way in both segments in question and discordant is the number of samples ordered differently.

$$\rho = 1 - \frac{6 * \sum d_i^2}{n(n^2 - 1)} \quad (5.3)$$

where ρ is the unitless Spearman rank correlation, d_i is the difference between the ranks of corresponding samples in the segments in question, and n is the number of samples in a 10-minute segment.

Pearson correlation coefficient assumes that the data being correlated are normally distributed and assumes linearity and homoscedasticity. Kendall and Spearman rank correlation do not assume a distribution for the data.

The FSM described in Section 3.5 was modified to be disabled if the absolute value of the correlation of the 10-minute segment containing the ST deviation measurement in question was below the set threshold. A threshold sweep was performed between 0 and 1, inclusive, in steps of 0.022 for a total of 46 threshold levels to match the number of threshold levels used with the SQVS_{EN}. Definitions of TP, FN, FP, and TN can be found in Section 3.9.

5.2.1 Results and Discussion

Table 5.1 shows the comparison of the TPs, FNs, FPs, and TNs detected in the unaltered signals and in the unaltered signals with gating applied using Pearson correlation coefficient at 0.3778, while Table 5.2 and Table 5.3 show the comparison using Kendall and Spearman rank, respectively. The threshold of 0.3778 was chosen since it maximized gating of FPs while minimizing TPs loss. The baseline performance of the bedside monitor was 78 TPs, 21 FNs, and 66 FPs.

Table 5.1 Comparing the TPs, FNs, FPs, and TNs detected in the unaltered signals and the unaltered signals with gating applied at 0.3778 using Pearson Correlation Coefficient

		Unaltered Signals With Gating Applied at 0.3778			
		TP	FN	FP	TN
Unaltered Signals	TP	70	8	N/A	N/A
	FN	0	21	N/A	N/A
	FP	N/A	N/A	29	37
	TN	N/A	N/A	0	N/A

Gating using Pearson correlation coefficient decreased FPs from 66 to 29 effectively stopping 56% of the FPs while only losing 8 TPs, approximately 10% of the total TPs. The FNs increased as the TPs decreased. The loss of the 8 TPs was attributed to spikes in the logged ST deviation measurements from the bedside monitor. The spikes led to a sharp

decline in the correlation coefficient of the 10-minute segments containing the spikes. These spikes can be as small as 0.5 seconds or as large as 10 minutes. The correlation coefficient typically recovered immediately (i.e. ≥ 0.3778) once the spikes were outside the 10-minute segment being correlated.

Gating using Kendall rank correlation led to the loss of 12 TPs, 15% of the total TPs. However, it maximized the gating of FPs by decreasing the FP count to 26, effectively stopping 67% of FPs. The Kendall rank correlation was more sensitive to a mismatch between the estimated trend and the bedside monitor measurements; thereby, it gated more TPs than using Pearson correlation coefficient.

Table 5.2 Comparing the TPs, FNs, FPs, and TNs detected in the unaltered signals and the unaltered signals with gating applied at 0.3778 using Kendall rank correlation

		Unaltered Signals With Gating Applied at 0.3778			
		TP	FN	FP	TN
Unaltered Signals	TP	66	12	N/A	N/A
	FN	0	21	N/A	N/A
	FP	N/A	N/A	26	40
	TN	N/A	N/A	0	N/A

Gating using Spearman rank correlation decreased FPs from 66 to 30 effectively stopping 55% of the FPs while only losing 7 TPs, approximately 9% of the total TPs. Using

Spearman rank correlation exhibited similar performance to using Pearson correlation coefficient; however, the additional TP was preserved at the cost of gating one less FP. Spearman rank correlation was chosen for further investigation since it balanced gating FPs with the loss of TPs.

Table 5.3 Comparing the TPs, FNs, FPs, and TNs detected in the unaltered signals and the unaltered signals with gating applied at 0.3778 using Spearman rank correlation

		Unaltered Signals With Gating Applied at 0.3778			
		TP	FN	FP	TN
Unaltered Signals	TP	71	7	N/A	N/A
	FN	0	21	N/A	N/A
	FP	N/A	N/A	30	36
	TN	N/A	N/A	0	N/A

Figure 5.8 is the visual representation of the changes in the count of TP, FP, and FN detected in the unaltered signals as the Spearman rank correlation threshold level was varied. The no gating case was at 0 threshold level, and the TP, FP, and FN counts were the same as the baseline operation of the bedside monitor. As the threshold level was increased, the FP count began to drop sharply at the expense of a slow decline in the TP count. The FN count increased as the TP count decreased. The data presented in Figure 5.8 were used to calculate Precision-Recall Curve shown in Figure 5.9. At the no gating case, the system exhibited recall of 0.79 and precision of 0.54. Gating at 0.3778 threshold level,

the solution's precision increased by 0.15 to 0.69, while, the recall decreased by 0.06 to 0.73.

Figure 5.8 TP, FP, and FN of all leads of all unaltered signals vs. absolute value of Spearman rank correlation threshold levels

Figure 5.9 Precision Recall Curve showing Precision and Recall of the unaltered signals alarm gating system based on absolute value of Spearman rank correlation

The 30 FPs remaining at the 0.3778 threshold level have been attributed to the conservative threshold level and the consistency of the trend of the logged bedside measurements with the estimated trend. The trend of the logged bedside monitor measurements stayed consistent with the estimated trend while it drifted outside of normal bounds (i.e. ± 0.1 mV). The bedside monitor measurements either drifted slowly or with a sudden jump in the measurements after which it immediately stabilized. Figure 5.10 shows an example of the slow drift of the bedside monitor measurements outside of normal bounds leading to a false alarm. Figure 5.11 shows a case of the sudden jump of the bedside monitor measurements outside of normal bounds leading to a false alarm.

Figure 5.10 Example of bedside monitor measurements (red) slow drift outside of normal bounds while matching the trend of the estimated trend (black) and ultimately the GS (blue). This example is from lead V2 of LTSTDB record 's20211'.

Figure 5.11 Example of bedside monitor measurements (red) sudden jump outside of normal bounds while matching the trend of the estimated trend (black) and ultimately the GS (blue). This example is from lead II of LTSTDB record 's20061'.

5.3 Integrating Trend Estimator with $SQVS_{EN}$

As discussed in Section 4.2, the $SQVS_{EN}$ has eliminated noise induced FPs while losing a single TP at an SQI of 6 dB threshold. Results discussed in Section 5.2 have shown that a Spearman rank correlation at the threshold of 0.3778 eliminated 55% of FPs due to misidentified fiducial points while losing only 7 TPs. The FSM presented in Section 3.5 was modified to be disabled when the SQI dropped below 6 dB and when the Spearman rank correlation dropped below 0.3778. The overall solution, $SQVS_{EN}^{TE}$, was tested on the test signals and using the test procedure described in Section 3.8.

Table 5.4 shows the effect applying the gating at 6 dB using SQI and 0.3778 using Spearman rank correlation. A total of 145 FPs out of 171 FPs were gated at the loss of 6 TPs out of the 77 TPs detected in the test signals. $SQVS_{EN}^{TE}$ attained a recall of 0.72 and a precision of 0.73. The precision increased by 0.42 from the bedside monitor performance on test signals while the recall decreased by 0.05. At 6 dB, $SQVS_{EN}$ had a precision of 0.58 and a recall of 0.77. $SQVS_{EN}^{TE}$ increased the precision by 0.15 and decreased the recall by 0.04. $SQVS_{EN}$ could have gated 147 FPs out of the 171 FPs at the expense of the loss of 27 TPs out of the 77 TPs.

Table 5.4 Comparing the TPs, FNs, FPs, and TNs detected in the test signals and the test signals with gating applied at 6 dB using SQIs and 0.3778 using Spearman rank correlation

		Test Signals With Gating Applied at 6 dB and 0.3778			
		TP	FN	FP	TN
Test Signals	TP	71	6	N/A	N/A
	FN	0	22	N/A	N/A
	FP	N/A	N/A	26	145
	TN	N/A	N/A	0	N/A

5.4 Summary

The bedside monitor has been found to misidentify fiducial point in AECG leading to false alarms. A trend estimator has been developed to estimate the trend of the ST deviation

measurements. The trend estimator was tested on the 16 LTSTDB records listed in Table 3.1 regarded as the GS. The trend estimator had a higher Pearson correlation coefficient over the bedside monitor across 15 out of the 16 LTSTDB records.

The trend estimator was used to estimate the ST segment deviation trend for the 16 LTSTDB records and then three correlation techniques were used to gate false alarms caused by misidentified fiducial points in the unaltered signals. The three correlation techniques were Pearson correlation coefficient, Kendall rank correlation, and Spearman rank correlation. The FSM was modified to be disabled when the absolute value of the correlation coefficient dropped below the set threshold. A threshold of 0.3778 was chosen since the gating of FPs was maximized while minimizing the loss of TPs. Using Pearson correlation coefficient gated 37 FPs out of the 66 FPs detected in the unaltered signals at the loss of 8 TPs. Using Kendall rank correlation gated 40 FPs out of the 66 FPs at the loss of 12 TPs. Using Spearman rank correlation gated 36 FPs out of the 66 FPs at the loss of only 7 TPs. Spearman rank correlation provided a good balance between gating FPs and preserving TPs.

The trend estimator was integrated with the $SQVS_{EN}$ system using thresholds 0.3778 and 6 dB, respectively. $SQVS_{EN}^{TE}$ successfully gated 145 FPs out of the 171 FPs at the loss of 6 TPs out of the 77 TPs found in the test signals. The recall and precision of the system were 0.72 and 0.73, respectively.

6 Chapter: Application of Signal Quality Analysis in an ECG Based Biometric System

Alphanumeric passwords are typically used to identify and authenticate users when using automated services such as online banking. However, increase in online fraud and computing power have decreased the efficacy of passwords in protecting sensitive data [63]. The prominence of passwords has faded in favor of more robust systems that are based on biometrics. Biometrics are personal physical characteristics that are unique to each individual such as the face, fingerprints, voice, and iris [20]. While the use of biometrics has been prominent in forensics, their utilization in a wide range of applications ranging from accessing the personal computer to identification and verification of travelers at border services has been the subject of research over the past decade [20], [64]. Some of the common biometric systems are based on fingerprints and are currently available for a common application such as personal computers; however, they have been the subject of spoofing and have become easier to replicate [20]. In 2001, Biel *et al.* suggested the use of ECG as a biometric [65]. Multiple studies have shown that an ECG is unique for every individual and as such can be utilized as a biometric [21], [65], [66]. By employing a portable ECG acquisition system, continuous verification and identification of users are possible; however, as discussed in Section 2.3.4, ECG can be affected by environmental and biological noise. This chapter discusses the integration of the SNR based SQI with an ECG biometric system in order to improve identification.

6.1 Methodology

6.1.1 Dataset

A total of 32 subjects were recruited from Carleton University student and academic body following the approval of the study by Carleton University Ethics Research Board. There were 23 males and 9 females with ages ranging from 21 years to 52 years. The only exclusion criterion of the study was the ability to run in place. Subjects were required to report their age, gender, height, weight, and any known cardiovascular diseases.

Five minutes of ECG data were continuously collected from each subject using the BioRadio Wireless Physiology Monitor, manufactured by Great Lakes NeuroTechnologies U.S.A., shown in Figure 6.1. The sampling rate was set to 500 Hz. ECG lead I was collected from each subject's hands using Ag/AgCl electrodes without conducting gel placed on a custom build pad shown in Figure 6.2. Subjects placed their right and left thumbs on lead I electrodes and their right-hand index finger on the ground electrode.

Figure 6.1 BioRadio Wireless Physiology Monitor manufactured by Great Lakes NeuroTechnologies U.S.A. [67]

Figure 6.2 Custom pad with Ag/AgCl electrodes without conducting gel placed for collection of lead I of ECG

A custom MATLAB graphical user interface (GUI) was used to collect the five minutes of ECG according to the following procedure:

1. 30 seconds of lying down
2. 30 seconds of sitting up
3. 30 seconds of standing still
4. 30 seconds of light movement
5. 60 seconds of standing still
6. 30 seconds of fast movement
7. 90 seconds of standing still

Each subject did at least two five minute recordings separated by a minimum of two months period. Table 6.1 lists the number of records available for each subject.

Table 6.1 Number of recordings per subject

Subject	Number of Recordings	Subject	Number of Recordings	Subject	Number of Recordings	Subject	Number of Recordings
1	4	9	4	17	3	25	3
2	4	10	3	18	3	26	3
3	3	11	3	19	3	27	3
4	3	12	3	20	3	28	2
5	4	13	3	21	4	29	2
6	4	14	3	22	4	30	2
7	3	15	4	23	3	31	2
8	3	16	3	24	4	32	2

6.1.2 Preprocessing

The ECG data were visually inspected, and the transitions between the steps in the procedure were removed to ensure a stable signal. The ECG data were then filtered using a third order zero-phase bandpass Butterworth filter with a low cut-off frequency of 5 Hz and high cut-off frequency of 50 Hz to maximize the attenuation of environmental and biological noise. A third order zero-phase bandstop Butterworth filter with a low cut-off frequency of 50 Hz and high cut-off frequency of 70 Hz was applied to specifically remove the 60 Hz powerline interference from the data.

6.1.3 Template Generation and Enrollment Database

Biometric systems for identification purposes are based on enrollment, where a template of a subject's data will be stored in a database for comparison purposes. In order to identify

a subject, a biometric system will compare the unknown data with the database, and the subject is identified when a match is found.

In this study, each subject was enrolled into the database using a template of their ECG data. The template was the ensemble average of the ECG data from each subject's first 30-seconds of standing still data from their first recording session. The R-waves were detected using Pan-Tomkins algorithm as described in Section 0. Each PQRST waveform was segmented as a 0.7-second window centered on the R-wave, and the ensemble average was performed as outlined in Section 3.4.3.1.

6.1.4 Identification Algorithm

Subjects were identified from their ECG using Wavelet distance measure which was proposed as an identification algorithm in [21]. The Wavelet distance measures the difference between two signals based on their wavelet coefficients. Wavelet distance measure was calculated as shown in (6.1).

$$WDIST_n = \sum_{p=1}^P \sum_{q=1}^Q \frac{|\gamma_a^{p,q} - \gamma_b^{p,q}|}{\max(\gamma_0^{p,q}, \tau)} \quad (6.1)$$

where $\gamma_0^{p,q}$ and $\gamma_n^{p,q}$ are the detail coefficients of the discrete wavelet transform, q , at the p th level of decomposition of the unknown data and the n th entry in the enrollment database, respectively. The τ is a threshold value set to minimize the effect of the small Wavelet coefficients from overemphasizing differences. The Daubechies scalar wavelet

(Db3) with a five-level decomposition was chosen since it was found to provide optimal value for ECG compression using wavelets [68]. The available online ‘Wavelet Dist’ function implemented in MATLAB was used as the implementation of the Wavelet distance measure algorithm [69]. The τ threshold value was left in default (0.25).

The unknown ECG was identified as the n th entry in the enrollment database with the smallest $WDIST_n$.

6.1.5 SQI Generation

Each record was divided into 20 seconds segments that were offset by 5 seconds. The segments were preprocessed to remove noise as described in Section 6.1.2. The R-waves were identified using Pan Tomkins as described in Section 0. The SQI for each segment was generated as previously described in Section 3.4.

6.1.6 Test Procedure and Analysis

The first recording which was used to enroll the subjects into the database was not used in the testing procedure. Data recorded while the subjects were standing, lightly moving, and standing after lightly moving (the third, fourth, and fifth steps in the procedure presented in Section 6.1.1) were segmented into 20-seconds segments offset by five seconds. Data within each 20-seconds segment were ensemble averaged to produce a beat representative of the segment as described in Section 3.4.3.1. The beat was then used as an input to the Wavelet distance measure algorithm and was compared to the templates stored in the enrollment database. A true positive (TP) was defined as the correct matching of the 20-

seconds segment with the correct subject's template in the enrollment database; conversely, a false positive was defined as the matching of the 20-second segment with the wrong subject's template.

SQIs were used to gate the results of the identification algorithm when a segment with low signal quality was presented to the algorithm. A segment with low signal quality was defined as a segment with an SQI below a set threshold. A threshold level sweep between -20 dB and 25 dB was performed where -20 dB represented no gating, and 20 dB represented extreme gating.

6.2 Results and Discussion

A total of 642 segments with 20 seconds duration were tested. The average SQI of preprocessed segments of the first standing step was 6.82 dB with the standard deviation (SD) of 3.84 dB; while the pre-processed segments from the standing step following light movement had an average SQI of 5.76 dB with the SD of 4.02 dB. The preprocessed segments from the light movement step had an average SQI of -4.98 dB with the SD of 2.01 dB which was indicative of the low signal quality and presence of high levels of noise. Figure 6.3 shows a segment representative of the average SQI of the first standing and the light movement steps before and after preprocessing.

Figure 6.3 An ECG segment from the first standing step representative of the average SQI from subject 25 third recording (top left) and the preprocessed version of the segment (bottom left). The top right shows an ECG segment from the light movement step representative of the average SQI from subject 01 fourth recording while the bottom right shows the preprocessed version of the segment.

At a -20 dB threshold level (i.e., no gating), the identification algorithm correctly identified 307 segments and misidentified 334 segments attaining a precision of 0.49. A single segment was not included in the analysis since the Pan Tomkins algorithm was unable to locate the R-waves in the segment. During the first standing and the standing following light movement steps the identification algorithm attained precisions of 0.80 and 0.68, respectively. The identification algorithm only attained an accuracy of 0.01 during the light

movement step. At 1 dB threshold level, the system gated 193 (57.8%) FPs out of 334 FPs at the loss of 25 (8.14%) TPs out of 307 TPs attaining a precision of 0.67; an increase of 0.18 over the no gating case. During the standing steps, the system only gated 38 (21.5%) FPs of the 177 FPs; on the other hand, the system gated 155 (98.7%) out of 157 FPs during the light movement step. The system retained all of the TPs detected during the light movement step. The results suggested that the system successfully gated the FPs due to low signal quality. The threshold 1 dB was chosen since it maximized the gating of FPs while minimizing the loss of TPs.

Table 6.2 shows a comparison between TP, FN (loss of TP), FP, and TN (absence of FP) between the no gating case and the gating at 1 dB case. Figure 6.4 is the visual representation of the changes in the count of TP and FP detected as the SQI threshold was changed.

Table 6.2 Comparing the TPs, FPs, and TNs detected in no gating case and with gating applied at 1 dB

		Biometric Identification With Gating Applied at 1 dB			
		TP	FN	FP	TN
Biometric Identification with no gating	TP	282	25	N/A	N/A
	FN	0	0	N/A	N/A
	FP	N/A	N/A	141	193
	TN	N/A	N/A	0	0

Figure 6.4 TP and FP of all segments vs. SQI threshold levels

The lost TPs exhibited signs of higher noise levels than retained TPs through visual inspection. The remaining FPs had SQIs greater than 1 dB which suggests that the noise levels were lower compared to other FPs. However, upon further investigation into the FPs not gated during the light movement step, it was discovered that even though the reported SQI was high, the individual ECG beats did not conform to a typical PQRST waveform shown in Figure 2.2. Figure 6.5 shows the beat generated by the ensemble average from the light movement step and the template of the same subject. Improvements to the data collection procedure such as lengthening the duration of each step may improve the quality of the ECG data. All of the FPs detected during light movement were gated at 2 dB threshold level. It was also discovered that the identification algorithm did match ECG data to the wrong subjects even though the ECG data have been deemed to be clean based on visual inspection. Figure 6.6 provides an example of ECG data when the identification algorithm matched the provided data with the wrong template.

Figure 6.5 Beat generated by ensemble average (blue) and template (red) from subject 17

Figure 6.6 ECG data for identification from subject 7 (blue), correct template from the database (black), and wrong template matched to the data according to the identification algorithm (red)

6.3 Summary

ECG biometrics have the potential of providing continuous identification of subjects; however, noise plaguing ECG can lead to a high number of FPs as shown in Figure 6.4. A large FPs count in a real world application may have resulted in the misidentification of a subject exposing sensitive data or locations.

The application of the SNR based SQIs was explored by integrating it with an identification algorithm. The system was tested on data collected from subjects' fingers while standing still and performing light movement. The identification algorithm attained an accuracy of 0.49 without the integration of the SQI. After the integration of the SQI and at 1 dB threshold level, the SQIs gated 57.8% of the FPs while losing 8.14% of the TPs attaining the precision of 0.67. The remaining FPs were found to have a relatively high SQI; however, the ECG beats did not conform to the typical ECG waveform which led to a misidentification. The identification algorithm was also found to have misidentified segments deemed by visual inspection and SQIs to have good signal quality.

7 Chapter: Conclusions and Future Work

7.1 Conclusions

The two objectives of this thesis were the reduction of false alarms in a commercial myocardial ischemia monitoring system and exploration of the application of ECG signal quality analysis in an ECG biometric system. Monitoring of ECG for signs of myocardial ischemia can lead to targeted application of β -Blockers and early intervention to prevent any damage to the cardiac tissue; however, noise has rendered the use of automated monitoring systems unfeasible. The high noise level led to a significant number of false alarms generated by the automated monitoring system. In this thesis, a standalone solution, SQVS_{EN}, was developed to gate false alarms by disabling the alarm generation stage based on an estimate of the signal quality of the ECG. The signal quality estimate, SQI, was based on the estimated ECG SNR. The solution was tested on 16 records from the LTSTDB online database randomly contaminated with noise from NSTDB. An investigation of the optimal SQI threshold level under which the alarms were gated suggested the use of 6 dB. SQVS_{EN} gated 100% of noise-induced alarms while losing a single true alarm at 6 dB threshold level. SQVS_{EN} attained a precision and a recall of 0.58 and 0.77, respectively, which was an increase in precision of 0.27 and a decrease in the recall of 0.01 from the commercial monitoring system performance. Further investigation in the ungated false alarms suggested that they were generated due to misidentification of ECG fiducial points by the commercial monitoring system.

To mitigate the issue of misidentification of ECG fiducial points, an algorithm was proposed to estimate the trend of the ST segment and correlate it with the trend of

measurements logged from the commercial monitoring system. The proposed trend estimator was tested against the trend of the ST segment measurements from the 16 records from the LTSTDB, and the proposed trend had a higher average Pearson correlation coefficient (r) with the LTSTDB than the trend of the measurements logged from the commercial monitoring system had with the LTSTDB. The average median of r of the trend estimator was 0.57 and 0.52 for lead II and lead V2, respectively, while the average median of r of the measurements from the commercial monitoring system was 0.41 and 0.37 for lead II and lead V2, respectively. The optimal correlation method and threshold were investigated by using the trend estimator to gate false alarms generated from the 16 records from the LTSTDB without contamination. The investigation suggested the use of Spearman rank correlation as the correlation technique and threshold level of 0.3778.

The trend estimator was integrated with the $SQVS_{EN}$ and was tested on the contaminated 16 records from LTSTDB. The overall system, $SQVS_{EN}^{TE}$, attained precision and recall of 0.73 and 0.72, respectively, which was an increase in precision of 0.42 and a decrease in the recall of 0.06 from the commercial monitoring system performance. $SQVS_{EN}^{TE}$ effectively gated 84.8% of all of the false alarms while losing 6 true alarms. Further investigation is required in the loss of the true alarms and the elimination of the remaining 15% of the false alarms; however, the current results satisfy the first objective set for this thesis.

The application of SQI was expanded beyond the myocardial ischemia monitoring system and was integrated with an ECG biometrics system in order to reduce the rate of false identifications. The ECG biometrics system with integrated SQI was tested on ECG data collected while subjects performed the light movement. The biometrics system had a precision of 0.49; however, the integration of the SQI raised the precision to 0.67 eliminating 98% of false identification during light movement (57.8% of total false identifications) while losing 8.14% of true identifications. The results satisfy the second objects set for this thesis; however, further investigation is required to analyze the effect of integration of SQI with biometrics system on ECG data with different level of noise and at different body positions.

7.2 Future Work

The work in this thesis has contributed to the reduction of the false alarms in myocardial ischemia commercial monitoring systems and the exploration of the application of signal quality analysis in ECG biometrics. More work is needed to improve the reduction of false alarms and to perform a more comprehensive investigation in ECG biometrics with ECG signal quality. The subsections below provide few recommendations of the work that can be conducted.

7.2.1 Investigation of Methods to Fuse Information from Trend Estimator and Commercial Monitoring System

The work in this thesis proposed that the trends from trend estimator and the commercial monitoring system to be fused together through correlation. The results showed promise;

however, not all false alarms were eradicated. These false alarms were not eradicated since the trends from the trend estimator and the commercial monitoring system correlated, but the measurements from the monitoring system were incorrectly in an alarm condition. The use of error measurements in the addition of the correlation techniques can be investigated to fuse the trends. The error measurements can have the potential of indicating when measurements from the commercial monitoring system are incorrectly in an alarm condition.

7.2.2 Application of Machine Learning to Integrate SVQS_{EN} and Trend Estimator

The SVQS_{EN} and trend estimator were integrated through checking if one of them was indicating that an alarm should be gated. They both had equal influence in deciding whether an alarm should be gated. The equal influence led to gating of true alarms even though the SVQS_{EN} indicated that the signal quality was acceptable. Investigation in the application of a smart voting system that will decide the level of influence of the SVQS_{EN} and the trend estimator can lead to the preservation of true alarms. The voting system can also allow the effective integration of other signal quality analysis algorithms.

7.2.3 Real Time Application of SVQS_{EN} and Trend Estimator in Clinical Environment

Currently, both algorithms were implemented in MATLAB environment which is designed to ease the design of algorithms but not the efficient implementation of them. The algorithms and systems proposed in this thesis should be implemented using efficient programming languages, such as C++. Additionally, the testing performed in this thesis

used signals with noise added to them which may not have been entirely representative of signals collected in a clinical environment. The performance of the proposed algorithms should be evaluated in a clinical environment which would account for the various types of noises and artifacts.

7.2.4 Investigation of Noise Levels and Body Position on ECG Biometrics Systems

In this thesis, the investigation of the performance of an ECG biometrics system with signal quality analysis was performed on noise level generated from light movement. The investigation was only limited to one type of movement and one body position. Further investigation is needed to assess the performance of the system on ECG signals with different noise levels. The ECG data used to investigate the integration of signal quality analysis with the biometric system was collected at various body positions and various movement types. The future investigation can utilize the various signals available in the database.

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