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Automatic Identification of Reliable Heart Rates from ECG Waveforms

by

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B.Eng., Communication University of China, 1996

A thesis submitted to the Faculty of Graduate Studies and Research

in partial fulfillment of the requirements for the degree of
Master of Applied Science in Biomedical Engineering

Ottawa –Carleton Institute for Biomedical Engineering (OCIBME)
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Abstract

Automatic estimation of heart rates (HR) from ECG data is an important technique used in diagnosis of various heart diseases. Whether the HR estimate is reliable is the premise for obtaining the accurate results.

Methods for quantifying the quality of ECG data for the purpose of automatic estimation of heart rates are exiguous. We propose two algorithms, SAECG and K-means reliability evaluation methods, for evaluating the reliability of HR estimates. Both methods compare PQRST segments to a pre-computed template using three distance measures including PRD, CCORR and WDIST resulting in reliability indices. We use three types of noise including baseline wander, EMG artifacts and motion artifact to contaminate clean ECG signals for testing. Results show that the reliability values correlate well with HR estimation errors. Both methods exhibit the ability to track the accuracy of HR estimation results, *i.e.* they can effectively reflect the quality of the ECG signals.

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Table of Content

Abstract.....	iii
Acknowledgement	iv
Table of Content	v
List of Tables	ix
List of Figures.....	x
List of Abbreviations	xviii
Chapter1. Introduction.....	1
1.1 Motivation.....	1
1.2 Objective.....	3
1.3 Contributions	4
1.4 Thesis Organization	5
Chapter 2. Background	7
2.1 Electrocardiogram (ECG).....	7
2.2 ECG Signal Processing Techniques for Heart Rate Estimation	10
2.2.1 Methods for ECG QRS Detection	11
2.2.2 Wavelet Transform Based QRS Detection	13
2.3 Evaluating the Reliability of Heart Rate Estimation	14
Chapter 3. ECG Data	17
3.1 Introduction.....	17
3.2 Synthetic Data.....	17

3.2.1	ECGSYN	17
3.2.2	Noise Signals	21
3.2.3	Synthetic ECG database.....	23
3.3	Real Data	23
3.3.1	MIT-BIH Arrhythmia Database.....	23
3.3.2	Person identification ECG Database.....	24
3.3.3	Ambulatory ECG data	25
Chapter 4. Heart Rate Estimation Algorithm		27
4.1	Introduction.....	27
4.2	Band-Pass Filter	28
4.3	Baseline Drift Removal	30
4.4	Continuous Wavelet Transform.....	31
4.4.1	Haar Mother Wavelet.....	32
4.4.2	Scale of the CWT	34
4.5	Threshold Setup	35
4.6	Heart Beat Detection.....	35
4.6.1	Whole Length Beat Detection (WLBD)	36
4.6.2	Segment Beat Detection (SBD)	36
4.7	R Peaks Positions.....	37
4.8	Heart Rate Estimation Effects	38
4.8.1	Effect of heart rate on heart rate estimation.....	38
4.8.2	Effect of PQRST shape on heart rate estimation	40

4.9	MIT-BIH ECG Data Test Result	47
4.10	Person Identification Data Test Results.....	49
4.11	Ambulatory Data Test Results.....	51
4.12	Discussion.....	54
Chapter 5. SAECG Reliability Evaluation		55
5.1	Introduction.....	55
5.2	Signal Average Electrocardiogram (SAECG)	56
5.3	PQRST Comparison	58
5.3.1	Percent Residual Difference (PRD)	58
5.3.2	Cross-Correlation Coefficient (CCORR).....	59
5.3.3	Wavelet Distance (WDIST).....	60
5.3.4	Find-Delay	61
5.3.5	Threshold Setup Measures.....	62
5.4	SAECG Reliability	65
5.5	ECGSYN Data Test Results	65
5.6	MIT-BIH ECG Data Test Results.....	72
5.6.1	MIT-BIH Arrhythmia ECG Data.....	72
5.6.2	Regression Analysis on Results	75
5.6.3	MIT-BIH Noise Stress Database	79
5.7	Ambulatory ECG Data Test Results.....	80
5.8	Discussion.....	82
Chapter 6. K-means Added Reliability Evaluation		84

6.1	Introduction.....	84
6.2	Sensitivity of SAECG Reliability on PQRST Shapes	84
6.3	K-means Added Reliability	87
6.3.1	K-means Clustering	87
6.3.2	K-means Added Reliability Method	88
6.3.3	PQRST Shapes Classification.....	90
6.3.4	K-means Reliability	93
6.4	K-means Reliability Results on ECGSYN Data.....	93
6.4.1	Effect on ECGSYN Data with Shape Varying PQRST Segments	93
6.4.2	Effect on ECGSYN Data with normal PQRST Segments.....	100
6.5	MIT-BIH ECG Data Test Results.....	104
6.5.1	MIT-BIH Arrhythmia ECG Data.....	104
6.5.2	Regression Analysis on Results.....	108
6.5.3	MIT-BIH Noise Stress Database	113
6.6	Ambulatory ECG Data Test Results.....	115
6.7	Discussion.....	117
Chapter 7. Conclusions.....		118
7.1	Summary	118
7.2	Future Work.....	120
References		122

List of Tables

Table 3. 1: ECGSYN Parameters	19
Table 4. 1: Heart rate estimation performance on ECGSYN database.....	40
Table 4. 2: Method Performance on MIT-BIH database	48
Table 4. 3: Comparison of several QRS detector performance on MIT-BIH database, data replicated from table 2 in [22], and this work is added.....	48
Table 4. 4: Test results on Person Identification Data	51
Table 5.1: Linear regression analysis results, where sse is sum of squared residuals; rsquare is the R^2 , square of cross correlation coefficient; dfe is degree of freedom; adjrsquare is dfe adjusted coefficient of determination; rmse is root mean squared error.....	78
Table 6.1: SAECG reliability scores of ECG data 102, 119 and 200 with shape varying PQRST segments	86
Table 6. 2: K-means added reliability scores of ECG data 102, 119 and 200 with shape varying PQRST segments	92
Table 6.3: Linear regression analysis results comparing SAECG and K-means reliability on QRS varying 9 MIT-BIH data, where sse is sum of squared residuals, rsquare is the R^2 , square of cross correlation coefficient, dfe is degree of freedom, adjrsquare is dfe adjusted coefficient of determination and rmse is root mean squared error	112

List of Figures

Figure 2.1: Action potentials from various regions of the heart. (Source picture is from [10], p49)	8
Figure 2.2: Typical ECG wave form (Source picture is from [4], P56)	9
Figure 2.3: Lead I,II,III electrodes placements. (Source picture is from [4], p15). RA represents right arm electrode, LA is left arm electrode. RL and LL are right leg and left leg electrodes.	10
Figure 3.1: Dynamical model used to generate synthetic ECG signals.....	19
Figure 3.2: ECGSYN generated ECG signal with default parameter values.	20
Figure 4.1: Heart rate estimation method	27
Figure 4.2: Magnitude and phase response of a 10th order Butterworth band-pass filter with the pass band 0.1-50Hz.....	28
Figure 4.3: Band-pass filtering of an ECG Signal, a) original ECG, and b) filtered ECG.	29
Figure 4.4: Baseline removal from an ECG, a) original ECG, b) baseline computed as a moving average of the original ECG, and c) baseline removed ECG.	31
Figure 4.5: The Haar wavelet.	33
Figure 4.6: A normal ECG segment and its CWT coefficient line using a Haar mother wavelet at scale 16.	34
Figure 4.7: WLBD Beats Errors and Heart Rate Errors at various HRs	39

Figure 4.8: SBD Beats Errors and Heart Rate Errors at various HRs	39
Figure 4.9: Morphed ECGs with T wave and HR increasing, a) morphed ECG data 1, b) morphed ECG data 10, and c) morphed ECG data 20.....	41
Figure 4.10: WLBD heart rate estimation results using synthetic data with different heart rate and T wave morphologies.....	42
Figure 4.11: SBD heart rate estimation results using synthetic data with different heart rate and T wave morphologies.....	42
Figure 4.12: Morphed ECGs with R Wave Width and HR Increasing, a) morphed ECG data 1, b) morphed ECG data 10, and c) morphed ECG data 20.....	43
Figure 4.13: WLBD Heart Rate Estimation Results Using Synthetic Data With Different Heart Rate and R Wave Morphologies.	43
Figure 4.14: SBD Heart Rate Estimation Results Using Synthetic Data With Different Heart Rate and R Wave Morphologies.	44
Figure 4.15: Morphed ECGs with P Wave Down, while T Wave Up and HR Increasing, a) morphed ECG data 1, b) morphed ECG data 10, and c) morphed ECG data 20	45
Figure 4.16: WLBD heart rate estimation results using synthetic data with different heart rate and P and T wave morphologies	46
Figure 4.17: SBD heart rate estimation results using synthetic data with different heart rate and P and T wave morphologies.....	46
Figure 4.18: SBD Heartbeats Detection Results on MIT-BIH Arrhythmia Data	47

Figure 4.19: WLBD heart rate estimation results using person identification data	50
Figure 4.20: SBD heart rate estimation results using Person Identification Data	50
Figure 4.21: Heartbeats detection result of “walking” task, a) Original ECG, b) Detection errors of heartbeats and HR	52
Figure 4.22: Heartbeats detection result of “jumping” task, a) Original ECG, b) Detection errors of heartbeats and HR	52
Figure 4.23: Heartbeats detection result of “arm motion” task, a) Original ECG, b) Detection errors of heartbeats and HR.....	53
Figure 5.1: Block diagram of the SAECG-based Reliability Evaluation	56
Figure 5.2: SAECG and PQRSTs segments used to compute the SAECG	58
Figure 5.3: Multi-SNR Signals Based on Data 122 Heartbeats Detection Result, a) Detected beats, b) added and missed beats errors of three types of noise	63
Figure 5.4: Reliability values for multi-SNR ECGs with BW noise added at 60BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values	66
Figure 5.5: Reliability values for multi-SNR ECGs with EM noise added at 60BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values	66
Figure 5.6: Reliability values for multi-SNR ECGs with MA noise added at 60BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values	67
Figure 5.7: Reliability values for multi-SNR ECGs with BW noise added at 80BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values	67
Figure 5. 8: Reliability values for multi-SNR ECGs with EM noise added at 80BPM, a)	

heartbeat detection errors, b) PRD/CCORR/WDIST reliability values	68
Figure 5.9: Reliability values for multi-SNR ECGs with MA noise added at 80BPM, a)	
heartbeat detection errors, b) PRD/CCORR/WDIST reliability values	68
Figure 5.10: Reliability values for multi-SNR ECGs with BW noise added at 100BPM, a)	
heartbeat detection errors, b) PRD/CCORR/WDIST reliability values	69
Figure 5.11: Reliability values for multi-SNR ECGs with EM noise added at 100BPM, a)	
heartbeat detection errors, b) PRD/CCORR/WDIST reliability values	69
Figure 5.12: Reliability values for multi-SNR ECGs with MA noise added at 100BPM, a)	
heartbeat detection errors, b) PRD/CCORR/WDIST reliability values	70
Figure 5.13: Reliability values for multi-SNR ECGs with BW noise added at 120BPM, a)	
heartbeat detection errors, b) PRD/CCORR/WDIST reliability values	70
Figure 5.14: Reliability values for multi-SNR ECGs with EM noise added at 120BPM, a)	
heartbeat detection errors, b) PRD/CCORR/WDIST reliability values	71
Figure 5.15: Reliability values for multi-SNR ECGs with MA noise added at 120BPM, a)	
heartbeat detection errors, b) PRD/CCORR/WDIST reliability values	71
Figure 5.16: Reliability values and detection errors of BW noise added multi-SNR ECGs	
from 48 MIT-BIH Arrhythmia ECG data, a) Reliability values, b) Detection	
errors	73
Figure 5.17: Reliability values and detection errors of EM noise added multi-SNR ECGs	
from 48 MIT-BIH Arrhythmia ECG data, a) Reliability values, b) Detection	
errors	74

Figure 5.18: Reliability values and detection errors of MA noise added multi-SNR ECGs from 48 MIT-BIH Arrhythmia ECG data, a) Reliability values, b) Detection errors	74
Figure 5.19: Linear regression with detection errors and PRD reliabilities of test results	76
Figure 5.20: Linear regression with detection errors and CCORR reliabilities of test results	77
Figure 5.21: Linear regression with detection errors and WDIST reliabilities of test results	77
Figure 5.22: 118e06 reliability evaluation result, a) Original noise stress ECG data 118e06, b) PRD reliability, c) CCORR reliability, d) WDIST reliability	79
Figure 5.23: SAECG reliability result for walking ECG signal. a) original ECG, b) detected heartbeats errors, c) reliability values	80
Figure 5.24: SAECG reliability result for jumping ECG signal. a) original ECG, b) detected heartbeats errors, c) reliability values	81
Figure 5.25: SAECG reliability result for arm moving ECG signal. a) original ECG, b) detected heartbeats errors, c) reliability values	81
Figure 6.1: SAECG and PQRST segments used to compute the SAECG of data 102	85
Figure 6.2: SAECG and PQRST segments used to compute the SAECG of data 119	85
Figure 6.3: SAECG and PQRST segments used to compute the SAECG of data 200	86
Figure 6.4: Block diagram of K-means Added Reliability Evaluation	89
Figure 6.5: Data 200 (0-30 seconds) centroid and PQRSTs of cluster 1	91

Figure 6.6: Data 200 (0-30 seconds) centroid and PQRSTs of cluster2	91
Figure 6.7: Data 200 (0-30 seconds) centroid and PQRSTs of cluster3	92
Figure 6.8: Generated ECG signal with multi PQRST shapes	94
Figure 6.9: Reliability for ECG data containing three different PQRST shapes contaminated with BW noise, a) Heartbeats detection errors, b) K-means reliability values, c) SAECG reliability values.....	95
Figure 6.10: Reliability for ECG data containing three different PQRST shapes contaminated with EM noise, a) Heartbeats detection errors, b) K-means reliability values, c) SAECG reliability values.....	96
Figure 6.11: Reliability for ECG data containing three different PQRST shapes contaminated with MA noise, a) Heartbeats detection errors, b) K-means reliability values, c) SAECG reliability values.....	97
Figure 6.12: Recalculated reliabilities of MA noise added multi-SNR ECG signals with varying PQRST shapes by using WDIST denominator threshold $\tau=0.01$ and WDIST measure threshold $\text{threshold}_{\text{WDIST}}=0.8$, a) Heartbeats detection errors, b) K-means reliability values, c) SAECG reliability values	99
Figure 6.13: Reliability values of BW noise added multi-SNR ECG signals with normal PQRST shapes at HR = 80BPM, a) Heartbeats detection errors, b) K-means reliability values, c) SAECG reliability values.....	101
Figure 6.14: Reliability values of EM noise added multi-SNR ECG signals with normal PQRST shapes at HR = 80BPM, a) Heartbeats detection errors, b) K-means	

reliability values, c) SAECG reliability values.....	102
Figure 6.15: Reliability values of MA noise added multi-SNR ECG signals with normal PQRST shapes at HR = 80BPM, a) Heartbeats detection errors, b) K-means reliability values, c) SAECG reliability values.....	
	103
Figure 6.16: SAECG and K-means reliability test results of BW noise added multi-SNR ECGs from 9 MIT-BIH Arrhythmia ECG data, a) SAECG reliability values, b) K-means reliability values, c) Heartbeat detection errors in percentage	
	105
Figure 6.17: SAECG and K-means reliability test results of EM noise added multi-SNR ECGs from 9 MIT-BIH Arrhythmia ECG data, a) SAECG reliability values, b) K-means reliability values, c) Heartbeat detection errors in percentage	
	106
Figure 6.18: SAECG and K-means reliability test results of MA noise added multi-SNR ECGs from 9 MIT-BIH Arrhythmia ECG data, a) SAECG reliability values, b) K-means reliability values, c) Heartbeat detection errors in percentage	
	107
Figure 6.19: Linear regression with detection errors and PRD reliabilities of SAECG test results on 9 MIT-BIH Arrhythmia ECG data.....	
	109
Figure 6.20: Linear regression with detection errors and PRD reliabilities of K-means added reliability test results on 9 MIT-BIH Arrhythmia ECG data	
	109
Figure 6.21: Linear regression with detection errors and CCORR reliabilities of SAECG test results on 9 MIT-BIH Arrhythmia ECG data	
	110
Figure 6.22: Linear regression with detection errors and CCORR reliabilities of K-means added reliability test results on 9 MIT-BIH Arrhythmia ECG data	
	110

Figure 6.23: Linear regression with detection errors and WDIST reliabilities of SAECG	
test results on 9 MIT-BIH Arrhythmia ECG data	111
Figure 6.24: Linear regression with detection errors and WDIST reliabilities of K-means	
added reliability test results on 9 MIT-BIH Arrhythmia ECG data	111
Figure 6.25: SAECG reliability method result on 119e06 of MIT-BIH noise stress	
database, a) Original noise stress ECG data 119e06, b) PRD reliability, c)	
CCORR reliability, d) WDIST reliability	113
Figure 6.26: K-means added reliability method result on 119e06 of MIT-BIH noise stress	
database, b) PRD reliability, c) CCORR reliability, d) WDIST reliability ...	114
Figure 6.27: K-means reliability result for walking ECG signal. a) the original ECG, b)	
the detected heartbeats errors, c) the reliabilities	115
Figure 6.28: K-means reliability result for jumping ECG signal. a) the original ECG, b)	
the detected heartbeats errors, c) the reliabilities	116
Figure 6.29: SAECG reliability result for arm moving ECG signal. a) the original ECG, b)	
the detected heartbeats errors, c) the reliabilities	116

List of Abbreviations

abs	Absolute Value
ADC	Analogue to Digital Converter
adjrsquare	Degree-of-freedom Adjusted Coefficient of Determination
Ag-AgCl	Silver-Silver Chloride
ANS	Autonomic Nervous System
A-V Node	Atrioventricular Node
BPM	Beats per Minute
BW	Baseline Wander
CCORR	Cross-Correlation Coefficient
CWT	Continuous Wavelet Transform
dfe	Degree-of-freedom
DWT	Discrete Wavelet Transforms
ECG	Electrocardiograph
EM	EMG Artifacts
EMG	Electromyograph
FN	False Negative
FP	False Positive
HR	Heart Rate
IIR	Infinite Impulse Response
LADT	Linear Approximation Distance Threshold
LVQ	Learning Vector Quantization
MA	Motion Artifacts
Max	Maximum
Min	Minimum
MLP	Multilayer Perceptron

MS	Microsoft
P^+	Positive Predictive Value
P1	Linear Square Fitting Coefficient 1
P2	Linear Square Fitting Coefficient 2
PPG	Photoplethysmogram
PRD	Percent Residual Difference
RBF	Radial Basis Function
rmse	Root Mean Squared Error
RR	Respiratory Rate
rsquare	Square of the Correlation Coefficient
S-A Node	Sinoatrial Node
SAECG	Signal Average ECG
SBD	Segment Beats Detection
Se	Sensitivity
SNR	Signal to Noise Ratio
SNR_{ECG}	Physionet Defined SNR for ECG
sse	Sum of Squared Residuals
Stat.	Statistic
STD	Standard Deviation
SVM	Support Vector Machine
TLFN	Time Lagged Feedforward Neural Network
TP	True Positive
WDIST	Wavelet Distance
WFDB	Waveform Database
WLBD	Whole Length Beats Detection

Chapter 1

Chapter1. Introduction

1.1 Motivation

The electrocardiograph (ECG) signal is associated with the electrical activity of the heart. It is the graphical expression of the electrical impulses that excite cardiac muscles in the form of a voltage-time waveform and is an important vital sign. ECG can be easily recorded with surface electrodes that are placed on specific points on the skin, and it is the most frequently used technique for measuring and diagnosing abnormal rhythms of the heart.

Diagnosis of many diseases can be performed through analysis of the ECG, including the heart rate and PQRST shape [1][2][3]. The electrical activity of a normal heartbeat originates from the sinoatrial node (S-A node). The heart rate can be influenced by many factors, including respiration, emotion, exercise, *etc.* Under abnormal conditions, the electrical activity may originate from another part of the heart, other than the S-A node. This deviation from the normal electrical activity of the heart is known as arrhythmia and can be life threatening [4][5]. Therefore, analysis of the ECG is very important.

Heart rate variability (HRV) is a measure of the variation of the heart rate, which has been shown to have clinical significance. Reduced HRV is usually associated with ventricular hypertrophy (LVH), myocardial infarction and diabetes [6].

Recording of ECG signals can be performed noninvasively using surface electrodes, however, noise and interference induced by bad electrode contact, motion artifact, EMG signals, or other sources can significantly lower the signal quality. Signal quality is a more significant problem with portable ambulatory monitors, which are becoming increasingly popular. Numerous algorithms have been developed for reliable heart rate estimation such as those in [7][8], however, these heart rate estimation algorithms focus on only detecting the heartbeats and the fact that noise may make the estimated HR becomes unreliable is neglected. Thus, a fast and effective algorithm to assess the reliability of the heart rate estimated from ECG is needed.

When an ECG signal is presented to a heart rate estimation method, a heart rate estimate can always be calculated. However, in the presence of noise, we cannot be sure how reliable the estimate is. Furthermore, with the increasing popularity of continuous and/or remote monitoring, there is an increasing amount of data being acquired. A method that can automatically calculate heart rates from ECGs contaminated with noise and assesses the quality of the data is necessary. Automated analysis is important to enable one to efficiently sift through the data. In addition, a measure of the reliability of the analysis is vital to find out how reliable the estimated HR is.

An earlier method was proposed to evaluate the ECG signal's quality in [9]. By calculating global features, every ECG signal is assigned a quality index. This method uses an extra reference heart rate monitor. It also utilizes a support vector machine (SVM) that requires an extensive training phase. Thus, the method is inappropriate for treating

large-scale ECG data. Hence, there is a need for a fast and effective method to evaluate the reliability of heart rate estimation from the ECG data

In this thesis, we undertake the task of devising a method that can be used to evaluate the reliability of heart rate estimation solely based on ECGs for monitoring purposes. Such a method should effectively filter out noise contaminated ECG segments that could lead to misdiagnosis, and ensure that the ECG data used are reliable and reflects the patient's actual conditions.

1.2 Objective

Our objective in this thesis is to devise an evaluation method that assesses the reliability of estimated HR or the quality of the ECG signal. In this thesis, we propose two reliability evaluation methods: Signal Average ECG (SAECG) reliability and K-means added reliability. These methods leverage the cyclical nature of the ECG, comparing the PQRST segments to a template by using three different distance measures: Percent Residual Difference (PRD), Cross-Correlation Coefficient (CCORR) and Wavelet Distance (WDIST). Prior to examining the reliability evaluation methods, we also devise a HR estimation method. The heart rate estimation method detects the R peaks of the ECG signal, corresponding to each heartbeat, and then estimates the HR by dividing the number of detected heartbeats by time.

Our framework includes the following aspects:

1. Devise a heart rate estimation method and evaluate its accuracy and robustness

to noise.

2. Devise a reliability evaluation method and evaluate its performance in the context of heart rate estimation.

1.3 Contributions

1) Proposed a novel reliability evaluation method based on SAECC

SAECC reliability method is suitable for assessing normal ECG signals. This method provides intuitive reliability values in percentage. Evaluation is performed on a number of ECG databases including: simulated ECG, MIT-BIH arrhythmia ECG database, ECG person identification database, and an ambulatory ECG database. We investigate the effect of baseline wander, electromyogram (EMG) artifacts, and motion artifact noise.

2) Proposed a novel K-means added reliability evaluation method.

K-means added reliability method is suitable for assessing ECG signals that contain shape varying PQRST segments. This method also provides intuitive reliability values in percentage, and has been extensively tested with several ECG databases as well as various types of noise as stated above.

3) Proposed a simple heart rate estimation method based on continuous wavelet transform (CWT).

Compared to other heart estimation methods, our method is simple, fast and highly accurate. We evaluated the effectiveness of the method on several ECG databases with various types of noise as mentioned above.

In addition to these above contributions, there were a number of minor or technical contributions, which will assist in furthering this research or other related research involved ECG.

The MIT-BIH arrhythmia database including forty eight 30-minute ECG signals have been converted to Matlab format. ECG signals' amplitude is in physical mV and the first channel has R peaks positions stored in same data.

All ECG recordings of the first 30 subjects in Person Identification ECG Database are manually examined and R peaks of heart beat peaks are marked out.

A group of ambulatory ECG signals were recorded specifically for this research, and heart beat peaks are manually marked out. These signals were examined with the proposed heart rate estimation method and reliability evaluation methods.

All the methods in this work have been implemented with Matlab programs which can be directly utilized for testing other databases.

Results of this research have been disseminated in:

G Ji, A.D.C Chan, A Cuhadar, "Heart Rate Reliability for the Smart Rollator", accepted by IEEE International Instrumentation and Measurement Technology Conference, Austin TX, 2010.

1.4 Thesis Organization

This rest of this dissertation is organized as follows:

In chapter 2, we provide background information regarding the ECG. The

techniques used in heart rate estimation are also introduced. Current achievements on evaluating reliability of heart rate estimation are discussed.

Then we describe the ECG datasets that are used to test and validate the proposed methods in chapter 3. For synthetic ECG signals, the procedure for generating the data is introduced. For real ECG data, the collection procedure and the conversion method are discussed. The introduction of noise into the signals is also explained.

In Chapter 4, we introduce the heart rate estimation algorithm based on the continuous wavelet transform (CWT). This method is extensively tested with various ECG datasets.

In Chapter 5, we describe our novel SAECG method for the evaluation of the estimated heart rates in terms of reliability. The method is tested and assessed with both synthetic and real ECG data.

Chapter 6 introduces K-means Added Reliability Evaluation method. This method is proposed to overcome the differences in PQRST shape. The method is also tested and assessed with both synthetic and real ECG data. We discuss the difference and improvements compared to the SAECG reliability evaluation method.

In the final Chapter 7, the results of this thesis are summarized and discussed. Suggestions for future research are also given in this chapter.

Chapter 2

Chapter 2. Background

2.1 Electrocardiogram (ECG)

The human heart consists of four chambers that pump blood through the body and maintain circulation. The heart's function is implemented by myocardial contractions. Action potentials produced by the depolarization and repolarization of the cardiac muscles are conducted in the heart and make the heart chambers contract in a highly synchronized order, alternating between systole and diastole. The electrical field produced by the action potentials can reach to the surface of the skin and can be measured and recorded with electrodes. The electrocardiogram (ECG) is a graphical illustration of the heart electrical signals in the form of voltage against time [10].

Cardiac muscles contract according to the stimulation of action potentials, which under normal circumstances are initiated by the sinoatrial node (S-A node). The propagating path is from the S-A node through the atria. The atria and ventricles are isolated from each other, except at the atrioventricular node (A-V node), which provides an electrical propagation path between them. The A-V node also causes a delay in the electrical propagation, which separates the physical contraction of the atria and the ventricles temporally. From the A-V node, the electrical propagation proceeds through the Bundle of His, the right and left bundle branches, the Purkinje fibers, and the ventricular muscle. The high speed propagation provided by the Bundle of His, the

bundle branches, and Purkinje fibers enable the entire ventricles to contract together. Figure 2.1 shows the action potentials in different parts. The recorded ECG is actually the aggregate electrical signal.

Figure 2.1: Action potentials from various regions of the heart. (Source picture is from [10], p49)

A typical ECG, with two heartbeats, is illustrated in Figure 2.2. The wave components for each heart beat are labeled with PQRST. Unlike Figure 2.1, there is no U wave in Figure 2.2. As the U wave is rarely seen in normal ECGs, it is not taken into consideration in the process of heart rate estimation [4]. Segments are the time durations between waves. Intervals are time durations between two designated waves.

Figure 2.2: Typical ECG wave form (Source picture is from [4], P56)

The ECG can be recorded using surface electrodes. Different electrode placements will yield different ECG waveforms. The placement of electrodes determines the view angle of the heart, referred to as “Lead”. A standard ECG electrode placement is the 12-Lead ECG, which is typically obtained with 10 electrodes. Usually, not all leads are needed, and a single Lead ECG recorded with 3 electrodes is commonly used. The 3 electrodes include a positive and a negative electrode, and the third one is the right-leg ground [4]. Figure 2.3 shows the electrodes placement of a 3-Lead ECG (Lead I, II and III), which is a subset of the 12-Lead ECG. For these Leads, the electrodes can also be attached to limbs.

Figure 2.3: Lead I,II,III electrodes placements. (Source picture is from [4], p15). RA represents right arm electrode, LA is left arm electrode. RL and LL are right leg and left leg electrodes.

The ECG waveform provides useful diagnostic information about the heart. The cardiac activity can be affected by movement or sleep, emotional state of the patient or a disease. If any part on the path that cardiac action potential conducts is blocked or acting independently due to disease or other reasons, the ECG waveform would have a corresponding change, which is known as an arrhythmia [4][5]. Normal HR is around 70 beats per minute (BPM), and the measure of HR variations around normal HR, namely HRV, is another significant index reflecting the cardiac health and autonomic nervous system (ANS) state [6]. Our goal is, however, not to analyze ECG waveforms for diagnosis of disease. In this thesis, we focus on devising methods to evaluate the reliability of the heart rates estimated from ECGs.

2.2 ECG Signal Processing Techniques for Heart Rate Estimation

Since Willem Einthoven created ECG in 1903 [11], along with the emergence of new technologies, there has been a considerable effort in developing methods for

automatic estimation of heart rates.

In the past, when computer technology was not as advanced as it is nowadays, the heart rate estimation methods were executed in hardware. Since QRS complex is the most distinct waveform of the ECG signal, detectors usually estimate heart rate by detecting QRS complexes or just the R peaks. A band-pass filter, or a combination of low-pass and high-pass filters, is commonly used to remove the low frequency noise and power line interference, as well as the baseline drift. For the QRS complex frequency range is between 4-25Hz and for P, T wave the range is between 0.5-10Hz [4][12]. Setting the band-pass filter on QRS complex frequency range not only reduces noise and interference but can also suppress the P and T wave. This preprocessing is still used in today's heart rate estimate methods. After the preprocessing, QRS or R peaks detection is performed. Hardware QRS detectors are fast and can work in real-time with ECG monitors.

Advances in computer technology enable the implementation of more complex HR estimation algorithms. Although methods for automatic ECG analysis exist in the literature, QRS detection is still important since detecting P or T waves is based on finding out the QRS complex first.

2.2.1 Methods for ECG QRS Detection

Many QRS detection methods exist in the literature. Pietka classified QRS detection methods as being syntactic or non-syntactic in [13]. Syntactic methods translate the ECG signal into strings, parse these strings with grammars, and then utilize

predefined patterns to perform the recognition. Most QRS detection methods are non-syntactic or mixed.

For non-syntactic categories, methods based on derivatives and digital filters are common. One of the early methods in this group was proposed by Pan and Tompkins [14]. This method is based on using a digital filter and adaptive thresholds to detect the QRS complex. Based on this, more involved methods were developed for better performance, such as [15] and [16].

Other methods based on artificial neural networks for QRS detection emerged in the 1990s including multilayer perceptron (MLP), radial basis function (RBF) and learning vector quantization (LVQ). An algorithm based on time lagged feed-forward neural network (TLFN) was proposed in [17]. This method utilizes matched filtering technique cooperating with TLFN to improve signal to noise ratio, and results show it can work well in noisy environment. Another algorithm based on linear-approximation distance threshold (LADT) compression with a back-propagation neural network was proposed in [18]. This method utilizes lines to approximate ECG with LADT algorithm, and then applies dual-edge threshold detection. Their results on MIT-BIH database show that the method effectively reduce the computational burden of applying neural networks, but it is not suitable for ECG signals that contain motion artifacts. Kohler *et al.* reviewed various software QRS detection methods in [12]. Additional algorithms include methods based on adaptive filter, hidden Markov models, mathematical morphology, matched filters, genetic algorithms, length and energy transforms and Hilbert transform based

QRS detection.

In this thesis we devise a heart rate estimation method based on continuous wavelet transform (CWT). Thus, wavelet transform based QRS detection methods are introduced in the following section.

2.2.2 Wavelet Transform Based QRS Detection

Mallat and Hwang applied wavelet transform on signals for analysis and processing. They proposed using local maxima of the wavelet coefficients for detecting and classifying the singularity in the signals [19]. Li *et al.* applied Mallat and Hwang's method for QRS detection in [20]. Afterwards, several wavelet transform based QRS detection methods derived from [19] were proposed using either continuous or discrete wavelet transform are used.

Wavelet based QRS detection methods usually utilize a band-pass filter or a combination of low-pass and high-pass filter to filter out noise in the ECG first. Then the transform is applied and the QRS complexes are detected by finding local maxima. Wavelet QRS detectors based on discrete wavelet transform (DWT) are given in [20] and [21], and those based on continuous wavelet transform (CWT) can be found in [22] and [23]. For a detailed review of wavelet based QRS detection methods, the reader is referred to [12].

The wavelet transform utilizes wavelets to approximate a signal. It can provide both time and frequency localization at different resolutions, hence it provides multi-scale and

multi-channel features. These features enable that, with a proper chosen mother wavelet and scale, the transform coefficient signal innately suppresses the P and T wave as well as low frequency noise. As a result, we can readily devise a fairly accurate and simple QRS detection algorithm. We chose CWT for heart beat detection because of the above advantages of CWT.

2.3 Evaluating the Reliability of Heart Rate Estimation

As explained in section 1.1, although algorithms for QRS detectors for heart rate estimation are abundant, methods for evaluating the reliability of the heart rate estimation results are sparse.

Recently, a method for evaluating the heart rate estimation was proposed in [9]. This method contains three main components: heart rate estimation algorithm, machine-learning waveform classifier, and a reference heart rate. The heart rate estimation algorithm is a simple peak detection method. This method is used to estimate the heart rate from the ECG and the photoplethysmogram (PPG). Machine-learning waveform classifier adopts support vector machine (SVM) to classify the ECG or PPG waveform as of good or bad quality. Reference heart rate is obtained from a vital-signs monitor. A decision-logic algorithm finally produces an integer quality index (range from 0 to 3) of the heart rate estimation result inferred from above three inputs.

The method in [9] provides a quality index to express heart rate estimation reliability, yet it has several limits. First, the method needs PPG and extra vital-signs

monitor to provide a secondary heart rate for comparison. Second, a SVM classifier is used. SVM needs training, and in order to train the classifier, human experts were employed to manually categorize ECG and PPG segments. Third, the quality index only has 4 grades, which may not provide enough resolution for categorizing ECG signals. These limitations make the reliability evaluation method complicated, with insufficient capability and, hence, it is not always applicable in practice, including this study. We neither have a reference HR nor the experts who can manually classify ECGs.

Another method employing a fuzzy logic algorithm to assess the reliability of heart and respiratory rate estimation in terms of confidence levels was proposed in [24]. Based on a 15 seconds time window, this method combines the heart rate (HR) and respiratory rate (RR) together and selects 10 features from them. Two of the features are the HR/RR ratio and the correlation between HR and RR. The remaining eight features include HR's mean value, RR's median value, HR and RR's slope (with least square regression), noise (derived from residuals) and signal interval. Member functions are designed to map these features to a value between 0 and 1. Finally, with predefined five rules, a fuzzy logic model produces confidence levels for HR and RR.

The fuzzy logic based method does not have a QRS detection module. The HR and RR values are obtained from a physiological monitor directly, and all the features are actually derived from HR and RR values. For some of the features such as HR and RR's mean, median and slopes, the member functions are based on a physiological range. It is possible that interference induced HR and RR variations still exist in a reasonable range,

and whether their fuzzy rule can discriminate the variations is not investigated. This method is developed for a vital-sign monitoring system where the respiratory rate is involved. Without RR, the feature selection and fuzzy rules may need to be re-devised. Due to the fact that HR and RR are directly obtained from monitors, the ECG and respiratory waveforms information are not available. So there is no way to manually annotate the signal for verifying the test result. Therefore, the method's true performance is not known, and the test result is more of a qualitative one. In addition, the test data contains only 8 subjects and the authors did not test the algorithm on a standard database to verify its performance.

From above discussion, we conclude that the current existing methods have limits. We need to devise new methods with the following desirable features: 1) Simple and fast; 2) Methods that do not need extra reference input and can provide effective reliability index solely from ECG data; 3) Methods that provide a reliability index in a common mathematical form, while providing sufficient resolution for quantifying signal quality. We also desire that the methods are extensively tested, especially with a standard ECG database to verify the performance. To achieve this goal, we propose two novel methods in this thesis which will be introduced in the following chapters.

Chapter 3

Chapter 3. ECG Data

3.1 Introduction

We need different ECG datasets to comprehensively test the two methods proposed for ECG heart rate estimation and reliability evaluation. In this study, we use both synthetic data and real data.

Synthetic data are obtained with an ECG generator based on a mathematical model [26]. By using this ECG generator, all the features of the ECG signal can be controlled, such as heart rate, PQRST wave amplitude and shape.

Real data are obtained from actual recordings of human subjects. Three ECG databases are used in this research. The first database is the MIT-BIH arrhythmia database, which consists of 48 annotated ECG signals. The second database is the Person Identification ECG database, which was used for a biometrics application [34]. The third database consists of ambulatory recordings recorded specifically for this research.

Various types of noise signals are also added to both the synthetic and real ECG data to examine the effects of noise.

3.2 Synthetic Data

3.2.1 ECGSYN

ECGSYN is an ECG waveform generator program. In this work, we used the Matlab implementation of this algorithm available on Physionet [25]. This ECG

generator is published in [26], and as a realistic ECG waveform generator, it is recommended by Physionet. This ECG waveform generator is based on a dynamical model, which uses three coupled ordinary differential equations to generate ECG signal. In addition to the heart rate, morphology and other features, the generator can also be used to set the signal's sampling rate and also be used to obtain R peaks positions. The ordinary differential equations are given in Equations 3.1, 3.2 and 3.3.:

$$\dot{x} = \alpha x - \omega y \quad 3.1$$

$$\dot{y} = \alpha y + \omega x \quad 3.2$$

$$\dot{z} = \sum_{i \in \{P, Q, R, S, T\}} \alpha_i \Delta \theta_i e^{-\frac{\Delta \theta_i^2}{2b_i^2}} (z - z_0) \quad 3.3$$

$$\text{where } \alpha = 1 - \sqrt{x^2 + y^2}, \Delta \theta_i = (\theta - \theta_i) \bmod 2\pi \text{ and } \theta = \text{atan2}(y, x)$$

This model draws a unit radius circle in the (x, y) plane of a three dimensional coordinate space and where the amplitude variation of the ECG is specified in the z direction. The angular velocity ω determines the heart rate, and the specific PQRST points are determined by parameter θ_i , while α_i and b_i determine the amplitudes and duration, respectively. Each revolution simulates one cardiac cycle, and repeating the circle generates the synthetic ECG signal. We can change the model parameters to obtain different ECGs.

Besides the morphology and heart rate variability, baseline wander can be controlled by Equation 3.4:

$$z_0(t) = A \sin(2\pi f_2 t) \quad 3.4$$

where A is the empirical value 0.15mV and f_2 is the respiratory frequency.

The Equations 3.1 to 3.3 are solved with a fourth-order Runge-Kutta integration with fixed time step $\Delta t = 1/f_s$, where f_s is the sampling rate. Using Matlab's ode45 solver, we can draw a single circle trajectory of the model as shown in Figure 3.1:

Figure 3.1: Dynamical model used to generate synthetic ECG signals.

The Matlab version ECGSYN presents as a function, with parameters and their default values summarized in Table 3.1. An ECG, as shown in Figure 3.2, can be generated with these default parameter values.

Table 3. 1: ECGSYN Parameters

Parameter	Description	Default Values
s	generated ECG signal (in mV)	n/a
ipeaks	labels for PQRST peaks, P(1), Q(2), R(3), S(4), T(5). Use <code>R=find(ipeaks==3)</code> to find the R peaks, <i>etc.</i>	A zero label is output if omitted,
sfecg	ECG sampling frequency	256 Hz
N_{beat}	Approximate number of heartbeats	256
anoise	Additive uniformly distributed measurement noise	0 mV

hrmean	Mean heart rate	60 BPM
hrstd	Standard deviation of heart rate	1 BPM
lfhfratio	LF/HF ratio	0.5
sfint	Internal sampling frequency	512 Hz
ti	The angle of each attractor (P, Q, R, S and T) around the limit cycle	[-70 -15 0 15 100] Degrees
ai	PQRST positions above or below the $z=0$ plane	[1.2 -5 30 -7.5 0.75]
bi	Gaussian width of peaks	[0.25 0.1 0.1 0.1 0.4]

Figure 3.2: ECGSYN generated ECG signal with default parameter values.

The MIT-BIH arrhythmia database has a sampling rate of 360Hz. The sampling frequency **sfecg** is also set to 360Hz for the synthetic ECG signals.

By changing the parameter **hrmean**, we can obtain ECG signals with different heart rates. To test our methods, we generated a series of ECGs with heart rate ranging from 40 BPM to 200 BPM with 5 BPM increment. Parameter N_{beat} controls how many beats generated. Since we vary the heart rate, a fixed N_{beat} value will generate different length ECG signals. As such, the heart rate and number of heartbeats are varied together to synthesize ECG signals that are at least 5 minutes in length.

Parameter **noise** adds noise to generated ECG waveform, but it only generates uniformly distributed random noise, which is not representative of real noise. As such, this parameter was not used. Other parameters were set to their default values.

3.2.2 Noise Signals

The MIT-BIH Noise Stress Test Database provides three types of noise: 1) baseline wander (BW), 2) EMG artifacts (EM), and 3) motion artifact (MA) [35]. The noise was recorded from real subjects. Each noise record is 30 minutes long and is representative of that noise type. These three noise signals are used as the noise source to contaminate clean ECG signals, and then we can generate signals with different levels of SNR.

WFDB (Wave Form Data Base) Software Package contains a group of tools that handle the Physionet signals. It also has been provided in several versions for different platforms. Its MS Windows version runs under the **Cygwin**, which is a UNIX simulator that runs under MS Windows [28].

Sigamp is a tool in WFDB that calculates a signal's amplitude value, which is then used to compute the SNR. For ECG signal amplitude, **sigamp** reads the first 300 normal QRS complexes. It sets the R peaks as the centre, measures the amplitude range values from 50ms before the R peak to 50ms after the R peak; the highest 5% and lowest 5% are discarded and the mean of remaining values is used as the ECG amplitude. The R peaks information is read from the 'atr' annotation file. For the noise signal amplitude, there is no R peak information. As such, **sigamp** divides the first 300 seconds noise signal to 1

second long segments and the mean amplitude and the root mean squared difference are calculated. The mean value of the middle 90% is used as the noise amplitude [29].

WFDB toolbox calculates the SNR with **nst** tool, and here we use the same definition from **nst**. The SNR here is not the same as the traditional concept. It is a measure defined to quantify the level of noise added to clean ECG signals, so the SNR_{ECG} is used and it is calculated using Equation 3.5:

$$SNR_{ECG} = 10 \log \frac{S^2/8}{(\alpha N)^2} \quad 3.5$$

where S is the ECG signal amplitude, N is the noise amplitude, and α is the scale factor for the noise. The ECG signal amplitude S is squared and then divided by 8 to get the QRS “power” estimate and the noise amplitude N is squared for calculating the SNR_{ECG} which is defined in [29].

With a given clean ECG, α is adjusted to obtain a particular SNR_{ECG} . The value of α can be derived from Equation 3.6:

$$\alpha = \frac{S/2N}{\sqrt{2 \cdot 10^{SNR_{ECG}/10}}} \quad 3.6$$

For three noise types (BW, EM and MA), the noise amplitude N is calculated with **sigamp** under **Cygwin**. For the ECG signal’s amplitude S , a new algorithm was created based on the **nst** definition, which reads R peaks positions rather than the ‘atr’ annotation file. R peaks positions are obtained along with the ECG generation. We multiply the noise signal with different values of the scale factor α and then add it to the clean ECG signal to generate a series of ECGs at different SNRs. Additive noise is the interference

that is uniformly distributed throughout signal frequency band whereas multiplicative noise is signal dependent and is difficult to remove without impairing the signal. Motion artifact is considered a source of a multiplicative noise in ECG signals. In practice, most of the noise in ECG signals are found to be additive [47]. Since we use the BW, EM and MA noise, the multi-SNR ECG generation method we use can represent a close simulation of real ECG signals.

3.2.3 Synthetic ECG database

For testing reliability evaluation methods, we generated a synthetic database consisting of ECG signals of different heart rates generated with ECGSYN, which were then contaminated by three different noise types (BW, EM, and MA). Four heart rates were used: 60, 80, 100 and 120 BPM. The SNR_{ECG} ranged from -6 dB to 24dB, with 1 dB increments. The generated clean ECG signals were 5 minutes in length. The synthetic ECG database consists of a total of 372 ECG signals ($4 \text{ heart rates} \times 3 \text{ noise types} \times 31 \text{ SNR levels}$).

3.3 Real Data

3.3.1 MIT-BIH Arrhythmia Database

The MIT-BIH arrhythmia database is available on Physionet. It provides a vast amount of data and tools to researchers for free and is well known in this field [30][31][12]. Several studies used the MIT-BIH database including [20] and [22].

The MIT-BIH arrhythmia database contains 48 ECG recordings from 2 leads, and with the result that each recording contains 2 channels of ECG signals. Only signals from the first channel are used in this work.

Each ECG data ‘dat’ comes with an associated header file ‘hea’ and annotation file ‘atr’. The header file provides information regarding the ECG data and the patient it was recorded from. The information includes the data record number, the sampling frequency, the number of samples, the gain and resolution of the ADC, the leads used to collect the signal, and the patient’s information and medication history [32]. The annotation file provides information regarding heartbeats, including their locations, which is used in this work to quantify the performance of the heart rate estimation and reliability evaluation.

All the MIT-BIH arrhythmia data are converted to Matlab format with the Physionet tool **PhysioNet_ECG_Exporter** [33], including the R peaks positions information. After entire conversion, we obtain a set of 48 ECG signals, 30 minutes in length, amplitude in mV, and sampled rate is 360Hz, with all heart beat locations added.

3.3.2 Person identification ECG Database

This database was originally built for the purpose of a biometrics application: ECG person identification [34]. Typically, ECG data is recorded using the electrode leads places on the chest or arms. In this database, ECG data were recorded by having subjects holding two Ag-AgCl electrodes on the pads of their thumbs. This was done to simplify the ECG data collection, making it more practical in person identification applications. However, recorded ECG signals are quite noisy as a result, which is a good for the purposes of this research.

Data were obtained from 60 subjects. Each subject participated in three ECG

recording sessions on three different days. A few subjects participated in one or two more follow up sessions. All the ECG signals are 90 seconds in length, amplitude in mV, with a sampling frequency of 1000Hz, using a 12-bit ADC (National Instruments, PCI-6071E). For ECG data where the sampling rate is not 360Hz, its specific sampling frequency is used in the Matlab program. ECG data were stored in Matlab format. Some patient's information were available (e.g. age and sex) but they were not used in this work.

These data are not annotated like the MIT-BIH data. Manual annotation was performed by the author of this thesis on all of the ECG recordings for the first 30 subjects. The data from the remaining 30 subjects were not used. The author has no special training in cardiology. As such, manual annotation may have errors due to the noise or irregularities in the PQRST shapes. As the subjects had no known cardiovascular disorders and the noise was typically not excessive, the manual annotation should be reasonably fair.

3.3.3 Ambulatory ECG data

The ambulatory ECG data were collected exclusively for our research. The data were recorded with a CleveMed model BioRadio 150 and the recording software was BioCapture. The recording sampling frequency is 600Hz. AC coupling was used and the ADC used a 12-bit resolution. A Lead-I configuration was adopted, with AgAgCl electrodes (model MVAP-II #FT002) placed on the chest near the armpits and a common ground was on the stomach near the right leg. Recorded ECG signal amplitudes were converted to mV.

Data were collected from one subject while undergoing three different tasks. The first task was a walking task. The signal contains alternating 50 seconds of walking and 10 seconds standing. The pace of walking is 1 step per second. A total of 303.18 seconds data were recorded for this task. The second task was a jumping task. The signal contains alternating 10 seconds of jumping and 20 seconds of standing. The pace of jumping is 1 jump per 2 seconds. A total of 129.34 seconds of data were recorded for this task. The third task was an arm motion task. The signal contains alternating 10 seconds of raising and lowering the arms from side to touch above head and 20 seconds of standing. The pace of arm movement is 1 second per cycle. A total of 129.40 seconds of data were recorded for this task. All the data were manually examined and the locations of the R peaks were annotated.

In the following chapters, we use the databases mentioned above to test our methods.

Chapter 4

Chapter 4. Heart Rate Estimation Algorithm

4.1 Introduction

In this research, we propose a heart rate estimation method based on the Continuous Wavelet Transform (CWT). The block diagram of heart rate estimation is shown in Figure 4.1:

Figure 4.1: Heart rate estimation method

Before the CWT, ECG signals are pre-processed to remove the power line interference and noise using a band-pass filter. This is followed by a baseline wandering removal process. These two steps help clean and suppress the noise in the ECG data.

When performing the CWT on ECG signals, the CWT coefficients line has distinct ridges corresponding to peaks in ECG signals. The CWT can be used to locate the R peaks that are the highest peaks in the ECG signal. The choice of the mother wavelet and transform scale factor is important to ensure that the resulting coefficients can effectively suppress the noise and P and T wave, while keeping the R peaks distinctive. A threshold is used to discern the R peaks, which are then used to estimate the heart rate.

4.2 Band-Pass Filter

A band-pass filter is used to filter out the noise. Most frequency components of an ECG signal are located in the range 0.1 to 50Hz [4]. A band-pass filter can be employed to remove any components outside this frequency range, including 60Hz power line interference.

In this work, an infinite impulse response (IIR) 10th order Butterworth filter was used, with a pass band from 0.1 to 50Hz. When the sampling frequency is 360Hz, the transfer function of the filter is Equation 4.1:

$$H(s) = \frac{0.0050229(s-1)^5(s+1)^5}{(s-0.3656)(s-0.9982)(s^2-1.997s+0.9972)(s^2-1.999s+0.9989)(s^2-0.7963s+0.2361)(s^2-1.041s+0.6183)} \quad 4.1$$

Its magnitude and phase response are plotted in Figure 4.2. To illustrate the low end amplitude frequency response, the horizontal axis is represented in log form:

Figure 4.2: Magnitude and phase response of a 10th order Butterworth band-pass filter with the pass band 0.1-50Hz.

The phase response is not a perfect straight line within the pass band. Therefore, the filter will change the shape of original signal slightly. However, this waveform distortion should not have a significant effect on the heart rate estimate. At both ends of the ECG signal, the filter process will change the waveform because of the finite number of samples. To reduce the filtering end effects, two 200 samples segments are added to both ends before the filtering. After the filtering process, these 200 samples segments are removed. Unlike zero padding, the 200 samples we used are the mirror segments from the head and the tail of the ECG signal. For many cases where an ECG signal does not start and end between T and P wave, zero padding will cause abrupt changes in the waveform and may generate false peaks. For ECG segments that are shorter than 200 samples, the added segment is the horizontal flipped version of itself. Figure 4.3 is an example of a segment of ECG signal passed through the band-pass filter:

Figure 4.3: Band-pass filtering of an ECG Signal, a) original ECG, and b) filtered ECG.

4.3 Baseline Drift Removal

Baseline drift is also known as baseline wander. It is caused by a variety of reasons, including patient movement (e.g. breathing), during ECG recording, and its frequency is around 0 - 0.8Hz [4]. It is a low frequency signal, which typically changes the absolute amplitudes of the signal. As a result, the P or T wave amplitude may be higher than R peak, which would lead to detection errors.

To remove the baseline wander, a moving average filter is used. The window size is set at 150 samples. This process removes high frequency components and provides the ‘baseline’ range information. Subtracting this baseline signal from the original ECG signal results in an ECG signal where the baseline wander is removed.

A band-pass filter is sufficient to remove the baseline wander, using a low-end cutoff frequency, which is higher than the common baseline wander frequency range. In this thesis, a two-step process was utilized: a band-pass filter followed by the baseline drift removal process. A comparison between this two-step process and filter-only (band-pass filter 1-50Hz) process showed that the heart beat detection rate was very close. The two-step process had a better positive predictive value and the filter-only method had better sensitivity, but the difference was around 1% or less. The two-step process had better performance on reliability evaluation since a narrower band-pass filter alters the signals much more, the main effect of which is reducing the differences between PQRST segments and hence increasing the reliability evaluation values especially in the low SNR_{ECG} range. Therefore, the two-step process was adopted.

Figure 4.4 shows the baseline wander removal result:

Figure 4.4: Baseline removal from an ECG, a) original ECG, b) baseline computed as a moving average of the original ECG, and c) baseline removed ECG.

4.4 Continuous Wavelet Transform

Wavelet transform includes continuous wavelet transforms (CWT) and discrete wavelet transforms (DWT). It is used in various applications, including image/video compression standards. In recent years, the wavelet transform has been used for biomedical signal analysis. It is a powerful tool that provides time-frequency information for analysis of signals that contain time-varied frequency components. Since DWT is not suitable for locating R peaks positions, in this work, we use the CWT. The CWT is defined in Equation 4.2:

$$X_w(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \Psi\left(\frac{t-b}{a}\right) dt \quad 4.2$$

where $\Psi(t)$ is the mother wavelet and $\mathbf{a}$, $\mathbf{b}$ are the dilation and location parameters, respectively. At a given scale $\mathbf{a}$, the CWT is computed by first placing the mother wavelet scaled by $\mathbf{a}$ at the beginning of the original signal. The mother wavelet is multiplied by the signal portion located in the mother wavelet window and the result is then integrated. The integration value is divided by $\sqrt{\mathbf{a}}$ to normalize the energy, resulting in a CWT coefficient. Subsequent steps move the mother wavelet with a time step of $\mathbf{b}$ (Matlab computes the CWT with $\mathbf{b}=1$) and the same process is repeated to compute other coefficients. This process is repeated till to the end of original signal to obtain the whole set of transform coefficients at scale $\mathbf{a}$. Plotting these coefficient values at a particular scale, produces a coefficient line, *i.e.* a transformed signal.

Lower scales of $\mathbf{a}$ depress the lower frequency components and keep higher frequency information in the coefficients; on the contrary, higher scales of $\mathbf{a}$ depress the higher frequency components and keep lower frequency information in the coefficients line. Therefore, with a properly chosen mother wavelet and scale factor $\mathbf{a}$, the CWT can keep the R peaks information in coefficients line, while sufficiently suppressing the P, T waves and noise.

4.4.1 Haar Mother Wavelet

Theoretically, an oscillatory small wave with $\int_{-\infty}^{\infty} \psi(x)dx = 0$ property can be a candidate mother wavelet. In fact, there are other restrictions. Many mother wavelet

families have been developed such as Morlet and Mexican Hat for various applications.

The Haar wavelet is defined in Equation 4.3 [36]:

$$\psi(t) = \begin{cases} 1 & 0 \leq t \leq 1/2 \\ -1 & 1/2 \leq t < 1 \\ 0 & \text{otherwise} \end{cases} \quad 4.3$$

Figure 4.5: The Haar wavelet.

Figure 4.5 is a plot of the Haar wavelet. The Haar wavelet, used in another QRS detection method [22], is chosen in this work as the mother wavelet to perform the CWT is due to two main considerations. The first one is that the ECG signals may contain positive, negative or irregular QRS complexes. The Haar wavelet lets a transformed QRS complex always have at least one positive peak, enabling QRS detection via a simple positive peak detection. The second is that for a normal ECG QRS complex, Haar wavelet only generates one negative and positive peak pair, which comes handy for detection purposes [22]. An ECG PQRS wave and its coefficient line of CWT transform obtained with Haar at scale 16 is shown in Figure 4.6.

Figure 4.6: A normal ECG segment and its CWT coefficient line using a Haar mother wavelet at scale 16.

By applying CWT on an ECG signal and then detecting the peaks in the coefficient line, which are associated with the R peaks, we can derive the R-R intervals. Although the peaks in the coefficient line are offset from the R peak, this will not affect the heart rate estimate as the bias is consistent throughout the ECG signal.

4.4.2 Scale of the CWT

Choosing the right scale factor value is important as it affects the method's accuracy. An earlier paper used dynamic scale values to perform CWT for QRS detection, and their dynamic scale values varied from 12 to 30 [22]. In our method, we use $a=16$ as the scale value, as a fixed value simplifies the method. This value was chosen based on empirical experimentation. By reducing multi scales of CWT to a single scale, the CWT can be considered as a simple filter.

4.5 Threshold Setup

Only the peaks that exceed the threshold in the CWT coefficient line are considered as candidate R peaks. Since R peaks are the highest peaks in the CWT transformed signal of a normal ECG, other peaks like P and T waves, as well as low amplitude noise are suppressed. Our threshold setting is based on the amplitude of the CWT coefficients line.

The threshold is the mean value of two sub-thresholds. The first sub-threshold is the half difference between the maximum and the mean value of the CWT coefficients line. The second sub-threshold is the standard deviation of the CWT coefficients line.

4.6 Heart Beat Detection

Heart beat detection is performed by applying a threshold to the CWT coefficient line. Any peak above the threshold is counted as a heartbeat.

A normal resting adult heart rate is under 100 BPM, but in some abnormal cases e.g. cardiac diseases, the heart rate could be higher than 300 BPM [4]. With this consideration, the distance of any two adjacent detected peaks is examined. If the distance shows that the heart rate exceeds a certain threshold, we consider that a noise peak is falsely detected as a heartbeat. In this case, this latest detected beat is discarded. We set this threshold to 230 BPM in our method.

4.6.1 Whole Length Beat Detection (WLBD)

Whole Length Beat Detection (WLBD) calculates the CWT on the entire ECG signal. Then the threshold is computed based on the coefficients values.

WLBD is suitable for short ECG signals. For long ECG signals, such as the MIT-BIH arrhythmia data (30 minutes in length), the WLBD is inapplicable. In a long ECG signal, a large baseline wander usually exists, and in different time duration, QRS amplitudes and noise peaks' amplitudes may have large discrepancies. Although our method applies the noise filtering and baseline drift removal first, there still exists a large amplitude variation that prevents the use of a single threshold value. Hence for long ECG signals, we use Segment Beats Detection.

4.6.2 Segment Beat Detection (SBD)

After noise filtering and baseline removal, Segment Beats Detection (SBD) divides a long ECG signal to several short segments, and then applies WLBD without filtering and baseline removal on each segment, successively. In this work, we use 10 seconds segment.

SBD effectively solves the problems caused by amplitude variation, but it also brings a new detection error. Since we use a 10-second time window to obtain ECG segments, the end of the window may be located in the middle of an R peak. This will

cause the same R peak to be counted twice in two successive segments, which leads to a false peak added to the total count.

To eliminate this error, we check if the end of the window is located on the trough of the ECG signal. If it is not, the method will expand the window size by 9 samples each time, until it finds that the end of the time window is on a trough. The decision is made when the last three samples' mean amplitude is higher than one third of the entire ECG samples amplitude's standard deviation. As actual ECG signals are complex, there still may be false beats detected.

We calculate the final heart rate estimate by dividing the number of heartbeats detected within an analysis segment by the segment's length in time.

4.7 R Peaks Positions

To evaluate our method's performance, we compare the detected heartbeats to the annotated heartbeats. ECGSYN and the MIT-BIH arrhythmia data provide R peak locations to compare R peak positions. For person identification data and ambulatory data, the R peak positions are manually annotated.

ECGSYN can provide the R peak positions when generating an ECG signal. The R peak detection results can be compared to these R peaks positions. It is possible to determine how many false beats were added and how many beats were missed, which can effectively be used to assess our method's performance.

MIT-BIH arrhythmia data are recorded ECG signals. Experts have manually checked all the ECG signals and annotated the R peak locations. We use this R peak position information for assessing the accuracy of our method.

4.8 Heart Rate Estimation Effects

4.8.1 Effect of heart rate on heart rate estimation

To examine the effect of heart rate, ECGSYN was used to generate synthetic ECG signals with heart rates ranging from 40BPM to 200BPM, with 5BPM increments and hence 33 ECG signals were generated. The signals length is set to approximately 5 minutes. There is no noise added to these signals. As the signal length is not too long both WLBD and SBD methods can be tested with these data. Heart rate estimation results using synthetic data with different heart rates are plotted in Figures 4.7 and 4.8. ECGSYN has 1 BPM standard deviation from the setup heart rate, so the generated ECG signal is not exactly the same as the setup value. For example, when the heart rate is set to 200 BPM, the actual generated ECG's heart rate may be 200.16 BPM (actual generated heartbeats divided by length). The setup value is used to plot the horizontal axis of the graphs. Each BPM value corresponds to an ECG data, and the heart rate error is calculated based on actual generated heart rate.

Figure 4.7: WLBD Beats Errors and Heart Rate Errors at various HRs

Figure 4.8: SBD Beats Errors and Heart Rate Errors at various HRs

The R peaks position comparison obtains the true positive (TP), false positive (FP) and false negative (FN) beats number. Thus we can use sensitivity $Se=TP/(TP+FN)$ and

positive predictive value $P^+ = TP/(TP+FP)$ to evaluate the method performance on ECGSYN data as shown in Table 4.1.

Table 4. 1:Heart rate estimation performance on ECGSYN database.

Method	Standard Total Beats	Added Beats	Missed Beats	TP	FP	FN	Se (%)	P ⁺ (%)	HR Errors (BPM)		
									Min(abs)	Max(abs)	STD
WLBD	33848	0	33	33815	0	33	99.90	100	0.12	0.12	0.00
SBD	33848	0	33	33815	0	33	99.90	100	0.12	0.12	0.00

From the results, we observe that for WLBD and SBD, the methods missed 1 beat on all ECG data. With the ECGSYN default settings, all the generated ECG ended with an R peak, and the CWT biases the peak positions to the right and out of the signal range.

We see that the WLBD and SBD have the same performance. Since only clean ECGs are used, the SBD added error does not show up. The detection rate with either method is higher than 99%, which is encouraging. In addition, the heart rate estimation error is less than 0.2 BPM. Since we estimate the HR by counting all the R peaks numbers then dividing it by total ECG length in time, the HR error is not affected by actual HR. In Figures 4.7 and 4.8, our method misses 1 beat on every ECG signal, and hence the results on every ECG data have same HR errors.

4.8.2 Effect of PQRST shape on heart rate estimation

We also obtained three groups of ECG signals, with different PQRST shapes. These data help us to find out if the PQRST morphology affects the heart rate estimation. Relatively short ECGs are created by setting the number of generated beats to 100.

Group 1 has 20 ECG signals, with the heart rate varying from 50 BPM to 145 BPM, with 5 BPM increments, and simultaneously the T waves are morphing from normal to high amplitude. This type of morphology can be seen in real ECG data, such as subject 8 in the Person Identification Database and data 107 and data 113 in the MIT-BIH database. Figure 4.9 illustrates the differences among these ECG signals.

Figure 4.9: Morphed ECGs with T wave and HR increasing, a) morphed ECG data 1, b) morphed ECG data 10, and c) morphed ECG data 20

The test results of heart beat detection errors on multi-HR ECG signals with increasing T wave morphology are plotted in Figures 4.10 and 4.11:

Figure 4.10: WLBD heart rate estimation results using synthetic data with different heart rate and T wave morphologies.

Figure 4.11: SBD heart rate estimation results using synthetic data with different heart rate and T wave morphologies

Group 2 has 20 ECG signals, with the heart rate varying from 50 BPM to 145, with 5 BPM increments, and the R waves' width increasing. This type of morphology can be seen in real ECG data such as data 104 and data 207 in MIT-BIH database. Figure 4.12 illustrates the differences among these ECG signals.

Figure 4.12: Morphed ECGs with R Wave Width and HR Increasing, a) morphed ECG data 1, b) morphed ECG data 10, and c) morphed ECG data 20

The test results of heart beat detection errors on multi-HR ECG signals with increasing R wave width morphology are plotted in Figures 4.13 and 4.14:

Figure 4.13: WLBD Heart Rate Estimation Results Using Synthetic Data With Different Heart Rate and R Wave Morphologies.

Figure 4.14: SBD Heart Rate Estimation Results Using Synthetic Data With Different Heart Rate and R Wave Morphologies.

Group 3 has 20 ECG signals, with the heart rate varying from 50 BPM to 145 BPM, with 5 BPM increments. We generated the waveforms such that the P waves are decreasing while T waves are increasing. This type of morphology can be seen in real ECG data such as data 213 in the MIT-BIH database. Figure 4.15 illustrates the differences among these ECG signals.

Figure 4.15: Morphed ECGs with P Wave Down, while T Wave Up and HR Increasing, a) morphed ECG data 1, b) morphed ECG data 10, and c) morphed ECG data 20

The test results of heart beat detection errors on multi-HR ECG signals with increasing T wave and decreasing P wave morphology are plotted in Figures 4.16 and 4.17:

Figure 4.16: WLBD heart rate estimation results using synthetic data with different heart rate and P and T wave morphologies

Figure 4.17: SBD heart rate estimation results using synthetic data with different heart rate and P and T wave morphologies

The proposed HR detection method detects R peaks, and naturally it should not be affected by the PQRST shape's change. From the WLBD test results on the above three groups of ECG data, the added or missed beats are less than 1 beat and the heart rate

estimation error is less than 1 BPM. SBD test results have SBD added errors, nevertheless the errors are negligible. Therefore, the detection accuracy is not related to the PQRST morphology, which verified our hypothesis.

4.9 MIT-BIH ECG Data Test Result

We use the 48 ECG signals to test our method. The MIT-BIH arrhythmia data are 30 minutes long, so we use SBD. The test result is given in Figure 4.18. The horizontal axis is ECG data number (from 1 to 48), corresponding to the MIT-BIH arrhythmia data number 100 to data number 234. Instead of plotting added/missed heartbeats, the averaged added/missed beats per segment are plotted to show the average errors on a segment. The signals are 30 minutes long, and with a 10 second test window, there are typically 180 segments for one ECG signal.

Figure 4.18: SBD Heartbeats Detection Results on MIT-BIH Arrhythmia Data

Table 4.2 gives the heart rate estimation method's sensitivity and positive predictive value on MIT-BIH arrhythmia database. The heart rate estimation is the average value over the 30 minute ECG signals.

Table 4. 2: Method Performance on MIT-BIH database

Standard Total Beats	Added Beats	Missed Beats	TP	FP	FN	Se (%)	P+ (%)	HR Errors (BPM)		
								Min(abs)	Max(abs)	STD
110159	438	1684	108475	429	1681	98.4740	99.6061	0	9.90	2.23

From the result, we observe that the heart rate estimation method has a good performance on real ECG data. Some data, such as the No.5 (data 104), No.29 (data 207) and No.43 (data 228), contain a large quantity of irregular PQRSTs such as ventricular flutter waves. Although for these data the missed beats number is higher than 200 beats, this corresponds to average missed heartbeats per segment. The method's overall sensitivity and positive predictive value are 98.47% and 99.61% respectively, and the heart rate estimation error has a 2.23 BPM standard deviation. In [22], Ghaffari *et al.* list a number of more involved methods in a table, which also includes the method proposed in [20]. We replicate the data from that table for comparison in Table 4.3:

Table 4. 3: Comparison of several QRS detector performance on MIT-BIH database, data replicated from table 2 in [22], and this work is added.

Database	QRS Detector	Se (%)	P+ (%)
MIT-BIH	From [22]	99.91	99.72
	From [20]	99.89	99.94
	Addison <i>et al.</i>	99.7	99.68
	Martinez <i>et al.</i>	99.80	99.86
	This work	98.47	99.61

As can be seen in Table 4.3, other methods show a 1% higher sensitivity and the positive predictive values are very close. In general, QRS detectors which have sensitivity and positive predictive values higher than 99% on standard ECG database are considered of the first rank of accuracy [12], so our method compares fairly well.

4.10 Person Identification Data Test Results

As explained in chapter 3, these ECG data are examined manually, and the R peaks positions are marked out for method performance evaluation. The counting result could have errors since the counter is not a cardiologist, and the result is for qualitative reference. The first 30 subjects' data are used. Each subject has three 90-seconds ECG signals, and thus we tested 90 ECG signals in total. The horizontal axis in the test result Figure 4.19 and 4.20 is ticked from 1 to 90 and every successive three data points correspond to an individual subject.

Figure 4.19: WLBD heart rate estimation results using person identification data

Figure 4.20: SBD heart rate estimation results using Person Identification Data

The following Table 4.4 gives the test results and statistic data. The Standard Total Beats here is the counted value.

Table 4. 4: Test results on Person Identification Data

Method	Standard Total Beats	Added Beats	Missed Beats	TP	FP	FN	Se (%)	P ⁺ (%)	HR Errors (BPM)		
									Min(abs)	Max(abs)	STD
WLBD	9968	269	109	9859	269	109	98.91	97.34	0	30.57	5.36
SBD	9968	434	176	9792	434	176	98.23	95.76	0	34	5.66

In this set of data, subject 14 (data 40, 41, 42) and subject 25 (data 74, 74, 75) have very noisy ECG recordings as well as subject 13 recording 1 (data 37) and subject 27 recording 2 (data 80). The test results on these data have large detection errors. Due to the relatively short ECG length, the detection errors on these data decrease the method's sensitivity and positive predictive value. The overall performance is still higher than 95%. Beside these noisy data, the average heart rate error on other ECG signals is less than 0.5 BPM.

4.11 Ambulatory Data Test Results

The ambulatory data are tested with SBD to comply with reliability methods. The heart rate estimation error is based on the 'standard' heart rate which was derived from manually examined R peaks. Test results for three tasks described in 3.3.3 are plotted as Figures 4.21, 4.22 and 4.23.

Figure 4.21: Heartbeats detection result of “walking” task, a) Original ECG, b) Detection errors of heartbeats and HR

Figure 4.22: Heartbeats detection result of “jumping” task, a) Original ECG, b) Detection errors of heartbeats and HR

Figure 4.23: Heartbeats detection result of “arm motion” task, a) Original ECG, b) Detection errors of heartbeats and HR.

For the walking task ECG, the signal is about 303 seconds. With a 10 second time window, the last segment for SBD is just 3 seconds, so one beat missed caused a big heart rate estimation error for this segment. From the detected heartbeats error, we can see that the method can overcome this kind of noise. Only the fifth walking period caused 1 false added beat. WLBD shows this added beat actually is from SBD added error that has been discussed in Section 4.6.2. The task ended up with standing, and the last segment has 1 beat missed. This missing beat is due to the CWT bias, which is the same as the case in Section 4.8.1.

For jumping and arm motion ECG, the actual heart rates are 99 and 94 BPM. So a 1 or 2 beat detection error still causes a big HR error in a 10 second window. In the

jumping task ECG, only the first jumping period has 3 false added beats and 4 missed beats. The other beats detection error occurs during the third and the fourth standing period, and the added and missed beats are still 1 beat respectively, which are from SBD added errors. In the arm motion ECG, the beat detection errors all occur during arm moving periods. The first arm moving period has 2 beats added; the second arm moving period has 2 beats added and 2 beats missed; the fourth arm moving period has 1 beat added and 1 beat missed. Like the second, third and fourth jumping period in jumping ECG, the third arm moving period in arm motion ECG has no detection error.

The overall HR estimation results for all ECG signals are close to actual value. We can see our HR estimation method is fairly accurate on ECG signals with body motion induced noise.

4.12 Discussion

Our heart rate estimation method performs well and is not affected by changes in PQRTS shape. The test result on standard MIT-BIH arrhythmia database shows its sensitivity is 98.47% and the positive predictive value is 99.61%. Compared to other more complicated detectors, ours is simple and fast while it is accurate. We will employ this heartbeat detection method to locate the PQRST segments for reliability evaluation which is introduced in the following chapter.

Chapter 5

Chapter 5. SAECG Reliability Evaluation

5.1 Introduction

The PQRST complex in an ECG of a healthy person has a well-defined shape if the measurement conditions are unchanged. Noise and interference induced by electrodes contact, motion, power lines, *etc.* may alter the shape of the PQRST in the ECG.

Assuming that the noise and interference are not correlated with the PQRST complexes, averaging multiple complexes would improve the signal to noise ratio. We can use this signal averaged ECG (SAECG) as a template for comparing all the PQRST complexes in the ECG. Thus, we can determine how many PQRST complexes are “good” and how many are “bad”, for a qualitative assessment of noise and interference present in the ECG. We can then use a metric (percentage) to represent how reliable the ECG signal is.

The block diagram for computing the SAECG-based reliability is shown in Figure 5.1. In this figure, three reliability evaluation scores are computed from three different distance measures (discussed in Section 5.3) that compare the PQRST complexes to the SAECG.

Figure 5.1: Block diagram of the SAECG-based Reliability Evaluation

5.2 Signal Average Electrocardiogram (SAECG)

The SAECG was proposed for person identification in [34]. An SAECG from a recording session was used as a template SAECG. A database of template SAECGs was constructed with each SAECG associated with a particular person. In subsequent ECG recording sessions, a new SAECG is computed and compared against the SAECGs in the database. A person is identified by having the SAECG template that is the most similar to the new SAECG. In this study, a similar concept of SAECG is used. We use the SAECG to evaluate the consistency of PQRST complexes in a single recording session.

By applying the heart beat estimation algorithm proposed in Chapter 4 to an ECG signal, we determine the location of the R peaks of each cardiac cycle. For each R peak position, a 512 ms segment is retrieved as the PQRST segment, with the R peak located at the center of the segment. Every two successive PQRST segments are compared by using a cross correlation to determine the time delay between the time segments (see section 5.3.4). The standard deviation of all the delay values is calculated. Any PQRST

segment with a delay value larger than the standard deviation is discarded as it is deemed to be an outlier. The remaining segments are averaged to produce the pre-SAECEG.

All the segments are compared to the pre-SAECEG by computing another cross-correlation. In the first comparison, the cross-correlation is performed between every two successive segments, from the first PQRSST segment to the end. Suppose a segment is of bad quality, because of excessive noise, and its previous and next segments are both of good quality. When the “bad” segment is compared to the previous one, a large delay value is obtained. When the next (good) segment is compared to it, there will still be a large delay value. This will result in “good” segments to be discarded. Similarly, two successive “bad” segments may have a small delay value, and then a “bad” segment may be kept for averaging. This second pass will remove those falsely kept “bad” segments and retrieve those falsely discarded “good” segments. After second comparison, PQRSST segments with a delay value larger than the standard deviation of all the delay values are discarded. The remaining PQRSST segments are averaged to produce the final SAECEG.

A sample SAECEG obtained from data 122 in MIT-BIH database is shown in Figure 5.2. The SAECEG computed from an analysis window will be used as the standard template to compare all the PQRSST segments within that analysis window.

Figure 5.2: SAECEG and PQRSTs segments used to compute the SAECEG

5.3 PQRST Comparison

PQRST comparison is implemented with three different distance measures to compare a PQRST segment with the SAECEG. These three measures are Percent Residual Difference (PRD), Correlation Coefficient (CCORR) and Wavelet Distance Measure (WDIST). These measures are computed separately and give three independent reliability values.

5.3.1 Percent Residual Difference (PRD)

PRD is used to compare two signals to find out the differences. It is commonly used in ECG related studies, such as ECG compression where the PRD is used to compare the reconstructed signal to the original [37][38][39][40]. In previous research, the PRD is defined in two different manners, and it is also referred to as the Percent Root

Mean Squared Difference. In this study, the PRD defined in [34] is employed as given in Equation 5.1.

$$PRD_n = \sqrt{\frac{\sum_{i=1}^M (x_0(i) - x_n(i))^2}{\sum_{j=1}^M (x_0(j) - \bar{x}_0)^2}} \times 100\% \quad 5.1$$

where x_0 is the SAECG and x_n is the n^{th} PQRS of the ECG signal, and M is the segment length.

For two segments being compared, a higher PRD refers to a bigger difference, whereas a lower PRD refers to a bigger similarity. Based on the definition, two identical segments would have a zero PRD value. However, PRD is sensitive to the segments' time alignment and to DC offsets. Two identical signals with shifts in either horizontal or vertical axis would have a high PRD value.

5.3.2 Cross-Correlation Coefficient (CCORR)

The cross-correlation coefficient (CCORR) is widely used in statistics to quantify the least squares fitting of the comparative data to the original template. CCORR is defined in Equation 5.2.

$$CCORR_n = \frac{\sum_{i=1}^M (x_0(i) - \bar{x}_0)(x_n(i) - \bar{x}_n)}{\sqrt{\sum_{j=1}^M (x_0(j) - \bar{x}_0)^2 \sum_{k=1}^M (x_n(k) - \bar{x}_n)^2}} \quad 5.2$$

where x_0 is the SAECG and x_n is the n^{th} PQRS of the ECG signal, and M is the segment length.

For two signals, a higher CCORR value represents a bigger similarity and a lower CCORR value represents a bigger difference. Two identical segments would have a CCORR value of 1.

5.3.3 Wavelet Distance (WDIST)

A wavelet distance (WDIST) measure was proposed in [34] which is a new measure to assess the similarity of two ECG signals. This measure uses the coefficients from a Discrete Wavelet Transform (DWT) to determine the similarity between two signals. WDIST is defined in equation 5.3.

$$WDIST_n = \frac{1}{PQ} \sum_{p=1}^P \sum_{q=1}^Q \frac{|\gamma_0^{p,q} - \gamma_n^{p,q}|}{\max(|\gamma_0^{p,q}|, \tau)} \quad 5.3$$

where $\gamma_0^{p,q}$ is the q^{th} SAECG's p level decomposition DWT coefficient, and $\gamma_n^{p,q}$ is the n^{th} PQRS segment's p level decomposition q^{th} DWT coefficient. Each level's DWT coefficients are obtained from the convolution of the signal with a pair of low-pass and high-pass decomposition filters. The absolute difference between two DWT coefficients is weighted by the relative amplitude of the DWT coefficients of PQRS segments. A threshold τ is used to eliminate very small coefficients. The default value of τ is 0.25.

The decomposition level is set as 5 and the wavelet ‘Db3’ is selected same as in [34]. For two signals, the lower WDIST value means bigger similarity and higher WDIST represents bigger difference.

5.3.4 Find-Delay

Find-delay employs the cross-correlation to estimate the temporal delay between two signals. In this research, ECG signals are sampled, and therefore the discrete cross-correlation is used.

Discrete cross-correlation is defined as:

$$r_{xy}(l) = \sum_{n=i}^{N-|k|-1} x(n)y(n-l) \quad 5.4$$

where $x(n)$ and $y(n)$ are finite causal sequences with length N , and $i=l$, $k=0$ when $l \geq 0$, and $i=0$, $k=l$ when $l < 0$ [41].

In our case, x and y are SAECG or PQRS segments. Cross-correlation shifts y and integrates it with x . When x and y are superimposed, the maximum value is obtained. Therefore, the shifting amount corresponding to the maximum integration value is the delay between these two signals.

The **find-delay** method computes the unbiased form of the cross-correlation and estimates the delay value as the location of the maximum value of the cross-correlation. The unbiased cross-correlation is calculated as in Equation 5.5. This value of the delay can be used to align two segments, temporally.

$$r_{xy,unbiased}(l) = \frac{1}{N - |l|} r_{xy}(l) \quad 5.5$$

5.3.5 Threshold Setup Measures

PRD, CCORR and WDIST are used for quantification of the detected PQRST segments' similarity to the SAECG. We also need to determine threshold values for this assessment.

Ideally, two identical PQRST segments would have PRD, CCORR and WDIST values of 0, 1, and 0 respectively. For segments that differ, the values increase for PRD and WDIST, and the values decrease for CCORR. A threshold is needed to indicate when the differences are deemed to be significant. To determine the proper thresholds for these three methods, a series of empirical tests are performed.

MIT-BIH Arrhythmia Data 122 is a clean signal with small baseline wandering. A group of multi-SNR signals are generated by adding different types of noise at different levels to data 122. Then, we use the heart beat estimation method to detect the R peaks. The SNR_{ECG} is set from -6dB to 24dB with 1 dB increments, and all BW, EM and MA noise are used.

Data 122 has 2476 heartbeats, and the detection result is plotted in Figure 5.3:

Figure 5.3: Multi-SNR Signals Based on Data 122 Heartbeats Detection Result, a) Detected beats, b) added and missed beats errors of three types of noise

From the result, we observe that at around 14dB, the detection result is very close to standard actual beats. Data with added MA noise have the highest detection errors at given SNR_{ECG} level. Suppose that 5% beats error rate is acceptable, so we can accept approximately 124 beats error. For data with MA noise, we find that at a SNR_{ECG} of 7 dB, 8 dB and 9 dB, the numbers of beat error are close to 124 beats. We calculate the PRD, CCORR and WDIST values between PQRSTs and the SAECG, and find the mean values of PRD, CCORR and WDIST at these SNR_{ECG} levels as:

$$PRD=73.45$$

$$CCORR=0.79$$

$$WDIST=0.24$$

These values are considered as the candidate thresholds. Several more tests are performed to amend these choices:

a) We use a regular PQRS segment, shift it along the horizontal axis and vertical axis and compute the PRD, CCORR and WDIST values by comparing the PQRS on shifted positions to the one in the original position.

b) We add random noise to the PQRS segment and calculate the PRD, CCORR and WDIST values by comparing noisy segments to the clean segment.

c) We add different levels of low amplitude random noise to PQRS segments while keeping R peaks noise free. PRD, CCORR and WDIST values are calculated by comparing noisy signals to the original one.

The above tests show that PRD is sensitive to either the position shifts or amplitude variation of the signal. WDIST is sensitive to the low amplitude random noise. CCORR is in the middle. Based on all test results, the thresholds of PRD, CCORR and WDIST are empirically determined as:

$$\text{Threshold}_{\text{PRD}}=75$$

$$\text{Threshold}_{\text{CCORR}}=0.80$$

$$\text{Threshold}_{\text{WDIST}}=0.20$$

It should be pointed out that WDIST value is subject to the absolute value of ECG amplitude. WDIST itself has no unit, yet the same ECG segment in different amplitudes will have different WDIST values. Above threshold configuration is only for ECG signals that the amplitude is in mV. If a PQRS segment has a PRD or WDIST value

above the threshold, the PQRS segment is considered as of a bad segment. For CCORR measure, a value below the threshold classifies the segment as of bad quality.

5.4 SAECG Reliability

SAECG reliability is computed separately for PRD, CCORR and WDIST. Any PQRS segment's PRD, CCORR and WDIST values are calculated by comparing it to the SAECG. Then the values are compared to the thresholds to determine whether the PQRS is of bad or good quality. The reliability metric is calculated using Equation 5.6:

$$Reliability_{PRD,CCORR,WDIST} = \left(1 - \frac{Number\ of\ Bad\ PQRSs}{Total\ Number\ of\ PQRS}\right) \times 100\ \% \quad 5.6$$

5.5 ECGSYN Data Test Results

ECGSYN is used to generate four 5-minute clean ECG signals with heart rates at 60BPM, 80BPM, 100BPM and 120BPM. Based on these ECG signals, multi-SNR signals are generated. Using a 5 minute long ECG signal allows us to use the WLBD method which can reduce the SBD added errors. The SNR_{ECG} is set from -6db to 24dB with 1 dB increments and three types of noise (BW, EM and MA) are used. Computing the reliabilities on these different SNR_{ECG} signals will help us to evaluate the performance of the proposed reliability evaluation method.

The test results on multi-SNR ECGs at 60BPM are plotted in Figures 5.4, 5.5 and 5.6. The heartbeat error plot is much more distinct than the HR error plot, thus the heartbeat error plot is used to reflect the detection errors. The added beats and missed

beats values are plotted based on actual standard heartbeats number to cooperate with detected heartbeats. Results of ECGs at other HRs are plotted in Figures 5.7 to 5.15.

Figure 5.4: Reliability values for multi-SNR ECGs with BW noise added at 60BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values

Figure 5.5: Reliability values for multi-SNR ECGs with EM noise added at 60BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values

Figure 5.6: Reliability values for multi-SNR ECGs with MA noise added at 60BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values

Figure 5.7: Reliability values for multi-SNR ECGs with BW noise added at 80BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values

Figure 5. 8: Reliability values for multi-SNR ECGs with EM noise added at 80BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values

Figure 5.9: Reliability values for multi-SNR ECGs with MA noise added at 80BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values

Figure 5.10: Reliability values for multi-SNR ECGs with BW noise added at 100BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values

Figure 5.11: Reliability values for multi-SNR ECGs with EM noise added at 100BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values

Figure 5.12: Reliability values for multi-SNR ECGs with MA noise added at 100BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values

Figure 5.13: Reliability values for multi-SNR ECGs with BW noise added at 120BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values

Figure 5.14: Reliability values for multi-SNR ECGs with EM noise added at 120BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values

Figure 5.15: Reliability values for multi-SNR ECGs with MA noise added at 120BPM, a) heartbeat detection errors, b) PRD/CCORR/WDIST reliability values

From the above test results, we observe that when SNR_{ECG} improves, the SAECG reliability evaluation results improve as well. The performance is consistent at different heart rates. Different noise types affect the reliability result in a different manner. BW does not seem to affect the HR estimate much except at very low SNR, which is expected. MA seems to have more of an effect than EM. PRD seems to underestimate reliability for BW considerably. CCORR and PRD underestimate reliability for EM. The three measures have similar scores for MA. WDIST measure has a much more consistent performance on different noise types. The reliability curves are not linear, but they are generally increasing functions of SNR_{ECG} . These results show that SAECG reliability evaluation method is effective for assessing the performance of heartbeat detection in noisy data, *i.e.* the quality of ECG signals.

5.6 MIT-BIH ECG Data Test Results

5.6.1 MIT-BIH Arrhythmia ECG Data

MIT-BIH arrhythmia ECG database contains forty-eight 30-minute dual-channel ECG data. The first channel of the ECG signal is used in this work. For each ECG signal, six level noise are added. Since this is a large data set, the SNR_{ECG} is set as -5, 0, 5, 10, 15 and 20dB with BW, EM and MA noise types.

We use SBD method and 10 seconds time window for the heartbeat detection. For each signal, the SAECG reliability is the average SAECG reliability value calculated

over all time windows. At a given SNR_{ECG} level, the overall reliability is the average value of all of the 48 ECG signals. Thus, error bars are plotted to show the standard deviations. Due to the large number of beats, the added and missed beat errors are presented as the percentage of total number of beats.

The reliability values and detection errors at different SNR_{ECG} are plotted as Figures 5.16, 5.17 and 5.18:

Figure 5.16: Reliability values and detection errors of BW noise added multi-SNR ECGs from 48 MIT-BIH Arrhythmia ECG data, a) Reliability values, b) Detection errors

Figure 5.17: Reliability values and detection errors of EM noise added multi-SNR ECGs from 48 MIT-BIH Arrhythmia ECG data, a) Reliability values, b) Detection errors

Figure 5.18: Reliability values and detection errors of MA noise added multi-SNR ECGs from 48 MIT-BIH Arrhythmia ECG data, a) Reliability values, b) Detection errors

This multi-SNR data set includes 864 (48 ECGs $\times$ 3 noise types $\times$ 6 SNR levels) 30-minute ECG signals. On such a large data set, the SAECG reliability evaluation result still can reflect the SNR_{ECG} variations, which can effectively classify the quality of the ECG signals. Looking at the detected heartbeat errors, we find that EM noise added multi-SNR ECG signals have the highest detection error. BW noise is mainly the baseline drift and it is no surprise that ECGs with BW noise have the lowest heartbeat detection error. ECGs with MA noise exhibit performance in the middle of the other two. However, the MA noise PRD reliability is higher than BW noise PRD reliability at -5dB. MA noise WDIST reliability is higher than EM noise WDIST reliability at -5dB, but lower for 0 to 20dB. This phenomenon indicates that the reliability score can be influenced by noise type. The similar phenomenon appears in test results on synthetic ECG in Section 5.5, where between 0 to 10 dB range, ECGs contaminated with EM noise have smaller heartbeat detection errors but the reliability values of PRD and CCORR are lower than ECGs with MA noise. Therefore, the reliability is a relative score and would not be an absolute score across different noise types.

5.6.2 Regression Analysis on Results

In practice, when an ECG signal is given, the noise type, SNR_{ECG} and R peak positions are not known. We can calculate the reliability scores, and if there is a linear relationship between the detection errors and the reliability scores, the calculated reliability score would be a representative of the error in the heart rate estimation. We

know that higher reliability scores correspond to lower detection errors, thus using regression analysis with linear squares fitting to find out the linearity between detection errors and the reliability scores would be valuable.

In this case, the total detection errors (in percentage form) are used as the regressors, and the reliabilities of three distance measures are the regressands. Regressors and regressands include BW, EM and MA noise all together. The actual detection errors versus PRD reliabilities are plotted in Figure 5.19, and the fitted line is in the same graph. CCORR and WDIST reliability scores and results of regression analysis are shown in Figures 5.20 and 5.21

Figure 5.19: Linear regression with detection errors and PRD reliabilities of test results

The correlation and goodness of fit is in Table 5.1.

Table 5.1: Linear regression analysis results, where sse is sum of squared residuals; rsquare is the R^2 , square of cross correlation coefficient; dfe is degree of freedom; adjrsquare is dfe adjusted coefficient of determination; rmse is root mean squared error

Distance Measure	Cross Correlation Coefficient	Fitted Line coefficient		Residuals			Goodness of Fit				
		P1	P2	Min(abs)	Max(abs)	STD	sse	rsquare	dfe	adjrsquare	rmse
PRD	-0.7126	-0.7033	61.93	0.6769	39.3768	20.68	7272.7	0.5078	16	0.4770	21.32
CCORR	-0.8008	-0.7202	73.4570	1.5709	37.9469	17.28	4401	0.6413	16	0.6188	16.5849
WDIST	-0.8595	-0.9279	81.6453	0.8181	30.7205	16.09	5078	0.7387	16	0.7224	17.8151

From Figure 5.19, 5.20 and 5.21, we observe that when the detection error increases, the reliabilities decrease. The fitted line drops to zero when the detection error is high enough. This relationship implies that all distance measures of SAECG reliability evaluation method can actually reveal the HR estimation error. From Table 5.1, the cross-correlation coefficients for detection errors and reliabilities of all distance measures are negative, which refers to the inverse ratio. The absolute value reveals the extent of correlation. WDIST has the highest absolute cross-correlation value, which is 0.8595, as well as best goodness of fit. Its fitted line can be expressed as in Equation 5.7:

$$y = -0.9279x + 81.6543 \quad 5.7$$

In Equation 5.7, x is the detection error, which is derived by comparing R peaks positions. When R peaks position is not known, we can use reliability scores to estimate the detection errors with this equation. For PRD and CCORR measures, the same procedure is applicable. With the regression analysis, we can quantify the detection using computed reliability scores, and this quantification would be across noise types.

5.6.3 MIT-BIH Noise Stress Database

MIT-BIH Noise Stress Database has multi-SNR ECG signals generated from MIT-BIH arrhythmia data 118 and 119. The EM noise is added after the first 5 minutes and thereafter exists every other two minutes. As a result, some ECG segments are clean. Therefore, when using the SBD on this signal, the noisy segments result in big errors while clean segments result in good estimations.

The MIT-BIH Noise Stress Database incorporates -6, 0, 6, 12, 18, 24dB SNR_{ECG} levels. From previous test results, we know that the detection error is acceptable when the SNR_{ECG} is above 15 dB. Data 118e06 can be used to depict the test result and it is plotted in Figure 5.22.

Figure 5.22: 118e06 reliability evaluation result, a) Original noise stress ECG data 118e06, b) PRD reliability, c) CCORR reliability, d) WDIST reliability

From the result, the PRD, CCORR and WDIST reliability measures clearly mark out the noisy segments. We expect to obtain similar results when applying the method to other noise stress signals at different SNR_{ECG} levels generated based on data 118.

5.7 Ambulatory ECG Data Test Results

ECG data described in Section 3.3.3 are used to show how the SAECG reliability evaluation method works on actual recorded ECG data. The ECG data contain segments of alternating moving and standing of the subject during recording. To assess the quality of different segments, we apply the SBD with a 10 second time window. The test results are plotted in Figures 5.23, 5.24 and 5.25.

Figure 5.23: SAECG reliability result for walking ECG signal. a) original ECG, b) detected heartbeats errors, c) reliability values

Figure 5.24: SAEKG reliability result for jumping ECG signal. a) original ECG, b) detected heartbeats errors, c) reliability values.

Figure 5.25: SAEKG reliability result for arm moving ECG signal. a) original ECG, b) detected heartbeats errors, c) reliability values

The walking ECG is a clean signal. The walking action does not have much effect on the ECG signal, so the heart rate estimation is accurate and the reliability values are nearly 100% on all segments. We observe that the noisy segments are clearly marked out with SAEKG reliability method. PRD and CCORR are more sensitive than WDIST measure. WDIST gives high reliability value at most noisy segments. We observe the heart beat detection error is fairly small. The highest added beats number for the jumping ECG is just 4 and for the arm ECG is 2. For the jumping signal the third and the fourth noisy segment have no beat detection error and for arm signal the fourth noisy segment has no beat detection error, but the reliability of PRD and CCORR are still low. This is because the noise is mainly from superimposed EMG and movement induced interferences. They are low amplitude noise and the original R peaks are not obscured with the noise, so the heart beat detection method still has the capability to detect the right R peaks. Since the shapes of PQRSST segments are changed, PRD and CCORR provide low reliability scores, but WDIST measure is not sensitive to this type of noise. The overall result shows that the SAEKG reliability evaluation method can correctly indicate the ECG signal's quality.

5.8 Discussion

Our results show that SAEKG reliability evaluation method is an effective measure to assess the normal ECG signal quality. A change in the SNR_{ECG} is accurately indicated by a change in reliability score. However, when the method is applied on ECG data that

contain PQRSs in varying shapes, the result shows that low reliability will be obtained even though the heartbeats detection is proven to be accurate. In the next chapter, we investigate K-means Clustering added reliability evaluation method.

Chapter 6

Chapter 6. K-means Added Reliability Evaluation

6.1 Introduction

The shape of PQRST segments in normal ECG waveforms can be considered consistent if the measurement conditions are unchanged. Thus, the SAECG reliability evaluation is an effective method to assess the signal quality. In some cases, the shape of PQRST segments might change for reasons not due to noise, but due to a cardiac disease or arrhythmia. This would cause the SAECG to have a large discrepancy from its constituent PQRSTs. The large discrepancy would result in a low SAECG reliability score. The heart rate estimation method, however, is not affected by the shapes of PQRST segments. Although, the PQRST shape changes within the ECG signal, the heart rate estimation result may still be accurate, which is not indicated in the low reliability score. With this consideration, we introduce the K-means added reliability evaluation method in this chapter.

6.2 Sensitivity of SAECG Reliability on PQRST Shapes

Several ECG signals in the MIT-BIH arrhythmia database contain varying shapes of PQRST segments, such as data 102, 119 and 200. Examining their SAECG and PQRST segments, the difference is obvious. Looking at three fragments from ECG data

102, 119 and 200 and applying WLBD to find R peaks, the PQRST segments can be retrieved. The SAECG and PQRST segments of data 102 (30-90 seconds) is shown in Figure 6.1. The SAECG and PQRST segments of data 119 (1245-1260 seconds) is shown in Figure 6.2. The SAECG and PQRST segments of data 200 (0-30 seconds) is shown in Figure 6.3.

Figure 6.1: SAECG and PQRST segments used to compute the SAECG of data 102

Figure 6.2: SAECG and PQRST segments used to compute the SAECG of data 119

Figure 6.3: SAECG and PQRST segments used to compute the SAECG of data 200

We apply the SAECG reliability evaluation method on above ECG fragments and obtain the reliability scores listed in Table 6.1:

Table 6.1: SAECG reliability scores of ECG data 102, 119 and 200 with shape varying PQRST segments

ECG data	SAECG Reliability (%)		
	PRD	CCORR	WDIST
Data 102 (30-90 seconds)	42.25	36.62	100.00
Data 119 (1245-1260 seconds)	57.14	78.57	100.00
Data 200 (0-30 seconds)	61.90	61.90	97.62

Although the heartbeat detection is accurate, as can be seen in Table 6.1, the distance measures PRD and CCORR give low similarity results. This is because the SAECG is averaged from various PQRST segments and hence has large differences from any of the constituent PQRST segments. Therefore, when we apply the SAECG reliability evaluation method on those ECG data with shape varying PQRST segments,

the reliability result would be sensitive to the change in PQRS segments which results in clean ECG signals having low reliability scores.

6.3 K-means Added Reliability

6.3.1 K-means Clustering

K-means clustering is a method that puts numerous points in an I-dimensional space into K clusters. A standard K-means clustering algorithm was proposed by Lloyd as a technique for least squares quantization in PCM [42]. Many optimized K-means clustering methods were proposed for speeding up the algorithm in [43] , [44], and [45].

Assuming there are two points X and Y in the I-dimensional space, then the coordinates of X and Y are $X(x_1, x_2, \dots, x_i)$ and $Y(y_1, y_2, \dots, y_i)$. The squared Euclidean distance between these two points is:

$$d(X, Y) = \sum_{i=1}^I (x_i - y_i)^2 \quad 6.1$$

Suppose that there are n points in the I-dimensional space and they are going to be divided into K clusters. Two iterative steps are used: assignment step and update step. Initially, for each cluster $S^{(k)}$, a random point $C^{(k)}$ is used as the initial centroid of this cluster. Equation 6.2 is the assignment step which assigns the point n to cluster $S^{(k)}$ by finding the nearest Euclidean distance which is defined by Equation 6.1:

$$S^{(k)} = \underset{k}{\operatorname{argmin}}\{d(C^{(k)}, X^{(n)})\} \quad 6.2$$

After the initial assignment step, each point temporarily belongs to a cluster. The update step then adjusts the centroid to match the mean of the constituent points for each cluster. The new centroid $C^{(k)}$ of cluster k is computed by Equation 6.3:

$$C^{(k)} = \frac{1}{|S^{(k)}|} \sum_{X^{(j)} \in S^{(k)}} X^{(j)} \quad 6.3$$

where $|S^{(k)}|$ is the number of points in cluster $S^{(k)}$. The assignment step and update step is then repeated until the point's assignments do not change [46].

In this research, the PQRS segment's length is chosen as 512ms. When the sampling frequency is 360Hz, the PQRS segment contains 184 samples. Each PQRS segment can be considered as a point in a 184-dimensional space. With K-means clustering method, PQRS segments are classified into K clusters and the centroid of each cluster is obtained.

6.3.2 K-means Added Reliability Method

When we examine the ECG data, we observe that although arrhythmia ECG signals contain shape varying PQRS segments, the variations of shape are not too numerous within a short period. The obvious variations of PQRS shape usually are less than 3 types, therefore, the K value is set to $K=3$.

We develop the K-means added reliability evaluation method to mitigate the effect that PQRST shapes have on the reliability results. The method utilizes the K-means clustering algorithm first to classify the PQRST segments into three clusters. Then the distance measures PRD, CCORR and WIDIST are calculated within each cluster. Instead of comparing PQRST segments to SAECG, PQRST segments are compared to the centroids calculated for each cluster.

Figure 6.4: Block diagram of K-means Added Reliability Evaluation

The block diagram of K-means added reliability evaluation method is depicted in Figure 6.4. The first block detects the R peaks of the ECG signal and obtains the PQRST segments in the same way as in SAECG reliability evaluation method. Afterwards, PQRST segments are classified into three clusters using the K-means clustering algorithm. Within each cluster, all the three distance measures are applied. The statistic units sum the numbers of bad PQRST segments over all the three clusters for each distance measure and calculate the reliabilities.

For WLBD method, the K-means clustering method classifies all PQRST segments for the entire ECG dataset. For SBD method, since we use a 10 second time window, there are a small number of PQRST segments for clustering. If the heart rate of an ECG signal is 60 BPM, then in a 10 second time window, there are only 10 beats. If these ten PQRST segments are similar, the K-means clustering method would possibly result in a cluster which only contains one or two PQRST segments or even an empty cluster. If there happens to be one or two noisy PQRST segments rather than shape varying segments in the 10 second window, then they will be classified into a cluster and be similar to the centroid, thus the reliability score is increased. Fortunately, noise usually has a random pattern and 3 clusters would not make all the noisy segments similar to centroids, so K-means added reliability evaluation is still applicable. When applying SBD, the time window should not be too small for K-means added reliability method, whereas SAECG reliability method can accommodate a shorter time window. Considering that normal heart rate is about 70 BPM, the time window should be no less than 5 seconds for SAECG reliability and no less than 10 seconds for K-means added reliability.

6.3.3 PQRST Shapes Classification

With K-means clustering algorithm, the shape varying PQRST segments of ECG signals such as data 102, 119 and 200 in MIT-BIH arrhythmia database can be classified into three clusters. For the whole length of ECG data 200 (0-30 seconds), the three clusters are illustrated in Figures 6.5 to 6.7.

Figure 6.5: Data 200 (0-30 seconds) centroid and PQRSTs of cluster 1

Figure 6.6: Data 200 (0-30 seconds) centroid and PQRSTs of cluster2

Figure 6.7: Data 200 (0-30 seconds) centroid and PQRSTs of cluster3

From the classification result illustrated in Figures 6.5, 6.6 and 6.7, we observe that within each cluster, the constituent PQRST segments are similar to the centroid. Thus, when we apply PRD, CCORR and WDIST measures to compare PQRST segments to centroids, the PQRST shape varying effect is eliminated. The K-means added reliability for the same data in Table 6.1 is listed in Table 6.2:

Table 6. 2: K-means added reliability scores of ECG data 102, 119 and 200 with shape varying PQRST segments

ECG data	K-means Reliability (%)		
	PRD	CCORR	WDIST
Data 102 (30-90 seconds)	94.37	94.37	100.00
Data 119 (1245-1260 seconds)	100	100	100.00
Data 200 (0-30 seconds)	97.62	97.62	100

6.3.4 K-means Reliability

After classifying PQRST segments with K-means clustering method into three clusters, the PRD, CCORR and WDIST are calculated between PQRST segments and the centroid in each cluster. The K-means reliability is given by Equation 6.4:

$$\begin{aligned} &K\text{-means Reliability}_{PRD,CCORR,WDIST} \\ &= \left(1 - \frac{\text{Sum Number of Bad PQRSTs over 3 Clusters}}{\text{Total Number of PQRSTs}}\right) \times 100 \% \quad 6.4 \end{aligned}$$

6.4 K-means Reliability Results on ECGSYN Data

We developed K-means added reliability evaluation method for eliminating the PQRST shape varying effect. For those ECG signals that only contain normal shape PQRST segments, K-means added reliability method could also be used. Next, we show the difference between K-means added reliability and SAECG reliability.

6.4.1 Effect on ECGSYN Data with Shape Varying PQRST Segments

ECGSYN can generate irregular PQRST shape ECG signals. Three 5 minute ECG signals with the same heart rate (HR=60 BPM) but different PQRST shapes are generated and then a 10 second segment is retrieved from each ECG signal in turn to form an ECG signal that contains multi PQRST shapes. The first 30 seconds of this ECG signal is shown in Figure 6.8:

Figure 6.8: Generated ECG signal with multi PQRST shapes

Based on this multi PQRTS shape ECG signal, a series of multi-SNR ECG signals are generated, and BW, EM and MA noise are all used to contaminate them. The SNR_{ECG} is set from -6dB to 24dB with 1dB increments. In total, ninety three ECG signals are generated.

To show the difference between K-means reliability and SAECG reliability, both methods are used. Since the signals are 5 minutes in length, only WLBD is used to avoid the SBD added errors. The heartbeat detection error of two methods are the same, thus just one result is plotted. The results are plotted in Figures 6.9 to 6.11.

Figure 6.9: Reliability for ECG data containing three different PQRST shapes contaminated with BW noise, a) Heartbeats detection errors, b) K-means reliability values, c) SAECC reliability values

Figure 6.10: Reliability for ECG data containing three different PQRST shapes contaminated with EM noise, a) Heartbeats detection errors, b) K-means reliability values, c) SAECG reliability values

Figure 6.11: Reliability for ECG data containing three different PQRST shapes contaminated with MA noise, a) Heartbeats detection errors, b) K-means reliability values, c) SAECEG reliability values

From the results, we observe that for the ECG signals with varying PQRST shapes, the PRD and CCORR reliability of SAECEG method do not reach 100% even though the SNR_{ECG} increases to 24dB and the heart rate estimates are perfect. The highest reliability value of PRD and CCORR is around 66% at $SNR_{ECG}=24dB$, although the heart beat detection error is zero. Interestingly, the WDIST reliabilities of both K-means and SAECEG method are similar. In K-means method, PRD and CCORR reliability increases

and reach 100% with the increased SNR_{ECG} , which effectively mitigates the effect of varying PQRST shapes. It has also been found that K-means added method slightly increases the reliability at the low SNR_{ECG} range, which verified the analysis in Section 6.3.2.

When we examine the results obtained with the WDIST measure, we notice that it exhibits similar performance in both SAECG and K-means added reliability method. This phenomenon is also shown in Table 6.1 and 6.2. Unlike PRD and CCORR, WDIST is a measure calculated using transform coefficients. From Equation 5.3, WDIST value is the weighted difference of DWT coefficients of two segments that are being compared. The wavelet is Db3 and the decomposition level is 5. For ECG signals, the PQRST segments' frequency components are mainly in the low frequency range. Furthermore, the PQRST's amplitude is small, thus usually the first level and second level decomposition coefficients are close to zero and below the default denominator threshold $\tau = 0.25$. The difference is mostly due to the fourth and the fifth level decomposition coefficients. With default denominator threshold, WDIST values between SAECG and PQRST segments, or between centroid and constituent PQRST segments, are usually less than 0.5. In Section 5.3.5, the threshold for WDIST measure is set to 0.2 to label a PQRST as good or bad. In actual cases, the shape variations of PQRST segments produce very small WDIST value changes. The change is too small to necessarily result in WDIST values exceeding the threshold. This make the WDIST measure resilient to the changes in PQRST shapes.

Setting a lower τ value will increase the WDIST value. The effect is equivalent to magnifying the WDIST values. If we let $\tau=0.01$, with the threshold setup method introduced in Section 5.3.5, the threshold for WDIST measure could be 0.8. With this new τ and threshold setup for both SAEKG and K-means added reliability method, we use the same multi-SNR ECG signals which were tested to generate Figure 6.11. We test the multi-SNR ECG signals to generate Figure 6.12:

Figure 6.12: Recalculated reliabilities of MA noise added multi-SNR ECG signals with varying PQRST shapes by using WDIST denominator threshold $\tau = 0.01$ and WDIST measure threshold $\text{threshold}_{\text{WDIST}}=0.8$, a) Heartbeats detection errors, b) K-means reliability values, c) SAEKG reliability values

From Figure 6.12, we observe that the WDIST reliability in SAECG method lost the resilience to shape varying PQRSTs, while performing well in K-means added method. Similar results can be obtained in BW and EM noise added multi-SNR signals. However, the default $\tau = 0.25$ is still adopted for three reasons: first, the default $\tau=0.25$ is effective for signal quality assessment. Secondly, default τ value let the test results be more informative. If an ECG segment tested with SAECG reliability method has a high WDIST reliability score while low PRD and CCORR reliability scores, it implies that the ECG signal contains shape varying PQRST segments. Thirdly, applying WDIST measure with a small τ which is lower than the default value will generate unsmoothed WDIST reliability curves.

6.4.2 Effect on ECGSYN Data with normal PQRST Segments

When we use K-means added reliability evaluation method on ECG signals that have stable PQRST segment shapes, most PQRST segments would be put into one cluster and the reliability should be close to that of the SAECG method. It has been verified that the heart beat detection method is not affected by heart rate. Therefore, we can use one series of multi-SNR ECG signals, which was used in chapter 5.4.1 to test the K-means added method. The series of multi-SNR ECG signals with HR = 80 BPM are used, and the test results are shown in Figures 6.13 to 6.15:

Figure 6.13: Reliability values of BW noise added multi-SNR ECG signals with normal PQRST shapes at HR = 80BPM, a) Heartbeats detection errors, b) K-means reliability values, c) SAEKG reliability values

Figure 6.14: Reliability values of EM noise added multi-SNR ECG signals with normal PQRS shapes at HR = 80BPM, a) Heartbeats detection errors, b) K-means reliability values, c) SAECEG reliability values

Figure 6.15: Reliability values of MA noise added multi-SNR ECG signals with normal PQRST shapes at HR = 80BPM, a) Heartbeats detection errors, b) K-means reliability values, c) SAEKG reliability values

The results show that K-means added reliability evaluation method provides similar reliability results on normal ECG signals. For BW noise added multi-SNR ECG signals, only the PRD measure has slightly higher reliability and CCORR and WDIST are almost the same as with the SAEKG method. For EM noise added multi-SNR ECG signals, PRD and CCORR measures both have higher reliability. Looking at the heartbeat detection errors on BW and EM noise added multi-SNR ECG signals, the detection error drops to

zero at 5 dB and 10 dB, respectively. K-means reliability provides higher values, thus it assesses the accuracy of the heart rate estimation better. For MA noise added multi-SNR ECG signals, the result is almost identical to the SAECG method. Again, WDIST measure has the best performance with both K-means and SAECG method.

The results show that K-means added reliability evaluation is suitable for either normal ECG signals or PQRST shape varying ECG signals. At low SNR_{ECG} range, K-means method slightly increases the reliabilities. However the reliability scores are still low, indicative of the lower SNR. The varying PQRST shapes effect is sufficiently mitigated.

6.5 MIT-BIH ECG Data Test Results

6.5.1 MIT-BIH Arrhythmia ECG Data

Not all the ECG signals in MIT-BIH arrhythmia database used in Section 5.6.1 contain shape varying PQRST segments. By manually examining all the 48 ECG signals, ECG data 102, 119, 200, 201, 203, 208, 221, 228 and 233 contain shape varying PQRST segments. Shape varying PQRSTs are also found in ECG data 213, 214, 215, 217, but the quantity of shape varying PQRST segments is relatively small, thus the former nine ECG signals are used for testing the K-means added reliability evaluation method and are compared to the SAECG reliability method. For 30-minute ECG signals, only the SBD method is used and the time window is set to 10 seconds.

SAECG and K-means reliability method have the same heart beat detection error.

For BW noise added multi-SNR ECG data, the SAECG reliability test results and the K-means reliability test results are plotted in Figure 6.16:

Figure 6.16: SAECG and K-means reliability test results of BW noise added multi-SNR ECGs from 9 MIT-BIH Arrhythmia ECG data, a) SAECG reliability values, b) K-means reliability values, c) Heartbeat detection errors in percentage

For EM noise added multi-SNR ECG data, the SAECG reliability test results and the K-means reliability test results are plotted in Figure 6.17:

Figure 6.17: SAECG and K-means reliability test results of EM noise added multi-SNR ECGs from 9 MIT-BIH Arrhythmia ECG data, a) SAECG reliability values, b) K-means reliability values, c) Heartbeat detection errors in percentage

For MA noise added multi-SNR ECG data, the SAECG reliability test results and the K-means reliability test results are plotted in Figure 6.18:

Figure 6.18: SAEKG and K-means reliability test results of MA noise added multi-SNR ECGs from 9 MIT-BIH Arrhythmia ECG data, a) SAEKG reliability values, b) K-means reliability values, c) Heartbeat detection errors in percentage

Compared to SAEKG reliability, the K-means reliability for all noise types in Figure 6.16, 6.17 and 6.18 can reach 100% at $\text{SNR}_{\text{ECG}}=20\text{dB}$. At lower SNR_{ECG} range, the K-means reliability values are higher by a small increment. For the EM and MA noise, the reliability values at -5dB are higher than that at 0dB . This is because at very low SNR_{ECG} range, the ECG signal has been completely submerged by noise. When the method detects the noise peaks and retrieves segments according to the peak positions, the retrieved noise segments would be similar to some extent, and thus it is possible that these noise segments exhibit high similarity to the cluster centroid. Above 0dB , the

reliability values are steadily increasing. EM noise added ECGs have the highest heartbeat detection error, but the K-mean reliability values are higher than BW noise added ECGs at -5dB. Similarly, MA noise added ECGs have lower K-means WDIST reliability than EM noise over 0 to 15 dB. As discussed in Section 5.6.1, for K-means added reliability, the reliability score can also be influenced by noise type and it is a relative score rather than an absolute score across noise types.

6.5.2 Regression Analysis on Results

As in Section 5.6.2, we can use linear regression analysis to compare SAEKG reliability and K-means reliability results. With heartbeat detection error in terms of percentage and average reliability values, including BW, EM and MA noise, the PRD actual detection errors versus reliabilities for SAEKG are plotted in Figure 6.19 and for K-means in Figure 6.20. The CCORR detection errors versus reliabilities for SAEKG are plotted in Figure 6.21 and for K-means in Figure 6.22. The WDIST detection errors versus reliabilities for SAEKG are plotted in Figure 6.23 and for K-means in Figure 6.24.

Figure 6.19: Linear regression with detection errors and PRD reliabilities of SAECD test results on 9 MIT-BIH Arrhythmia ECG data

Figure 6.20: Linear regression with detection errors and PRD reliabilities of K-means added reliability test results on 9 MIT-BIH Arrhythmia ECG data

Figure 6.21: Linear regression with detection errors and CCORR reliabilities of SAECG test results on 9 MIT-BIH Arrhythmia ECG data

Figure 6.22: Linear regression with detection errors and CCORR reliabilities of K-means added reliability test results on 9 MIT-BIH Arrhythmia ECG data

Figure 6.23: Linear regression with detection errors and WDIST reliabilities of SAECD test results on 9 MIT-BIH Arrhythmia ECG data

Figure 6.24: Linear regression with detection errors and WDIST reliabilities of K-means added reliability test results on 9 MIT-BIH Arrhythmia ECG data

The cross- correlation coefficients, fitted line coefficients and goodness of fit for these methods are given in Table 6.3.

Table 6.3: Linear regression analysis results comparing SAECG and K-means reliability on QRS varying 9 MIT-BIH data, where sse is sum of squared residuals, rsquare is the R^2 , square of cross correlation coefficient, dfe is degree of freedom, adjrsquare is dfe adjusted coefficient of determination and rmse is root mean squared error

Distance Measure	Method	Cross Correlation Coefficient	Fitted Line Coefficient		Residuals			Goodness of Fit				
			P1	P2	Min(abs)	Max(abs)	STD	sse	rsquare	dfe	adjrsquare	rmse
PRD	SAECG	-0.6728	-0.5227	47.35	2.0702	30.4985	16.6431	4708.9	0.4527	16	0.4185	17.1553
	K-means	-0.5981	-0.5005	78.77	0.1209	47.2631	19.4147	6407.8	0.3578	16	0.3176	20.0122
CCORR	SAECG	-0.7662	-0.5271	57.48	0.3459	23.8105	12.8006	2785.6	0.5871	16	0.5613	13.1946
	K-means	-0.6351	-0.4145	85.5	2.3879	34.8125	14.5948	3621.2	0.4034	16	0.3661	15.0440
WDIST	SAECG	-0.8569	-0.9404	78.68	0.5990	34.6891	16.3827	4562.7	0.7342	16	0.7176	16.8869
	K-means	-0.8608	-0.8404	91.51	0.1705	31.2719	14.3852	3517.9	0.7410	16	0.7248	14.8279

SAECG and K-means reliability all decrease along with an increase in detection error. K-means reliability effectively increases the reliability values for QRS varying ECG signals. In Table 6.3, P2 is the reliability value when zero error occurs. We can see for all distance measures, the K-means reliability have significantly increased P2s. The K-means added reliability is proposed to remedy the PQRST shape varying problem and it in fact does the job, but it also increases the reliability values at low SNR_{ECG} range. From Table 6.3, we find that for PRD and CCORR, the cross-correlation coefficients and the goodness of fit for K-means added method are worse than SAECG method. The main factor for this effect is that the K-means added reliability has an inverse curve at low SNR_{ECG} range. This phenomenon is analyzed in Section 6.3.2 and also pointed out in Section 6.5.1. WDIST again exhibits outstanding performance. Its K-means reliability

values have the best correlation coefficient with detection errors and better goodness of fit than SAECG.

6.5.3 MIT-BIH Noise Stress Database

In Chapter 5, the ECG signal data 118e06 of MIT-BIH noise stress database was used to show that the SAECG reliability method has the capability to indicate presence of the noisy segments. Data 119 contains shape varying PQRST segments, thus the 119 series noise stress signals can be used to show the difference between SAECG and K-means reliability method.

Data 119e06 is used to perform the test and the results are plotted in the following figures. The result of SAECG reliability method on data 119e06 is given in Figure 6.25:

Figure 6.25: SAECG reliability method result on 119e06 of MIT-BIH noise stress database, a) Original noise stress ECG data 119e06, b) PRD reliability, c) CCORR reliability, d) WDIST reliability

The result of K-means reliability method is plotted in Figure 6.26:

Figure 6.26: K-means added reliability method result on 119e06 of MIT-BIH noise stress database, b) PRD reliability, c) CCORR reliability, d) WDIST reliability

From the above figures, we observe that K-means added reliability method offers a significant improvement on indicating the noisy segments, especially for PRD and CCORR measures. Still, WDIST has better performance than PRD and CCORR on handling ECG signals containing shape varying PQRST segments with the SAECG method. In K-means added reliability method, the WDIST measure result also has an obvious increase. Similar results can be obtained with the other 119 series signals in the MIT-BIH noise stress database.

6.6 Ambulatory ECG Data Test Results

The same ECG signals used in Section 5.7 are used for K-means added reliability evaluation method. The SBD time window is 10 seconds. The test results are plotted in Figures 6.27, 6.28 and 6.29.

Figure 6.27: K-means reliability result for walking ECG signal. a) the original ECG, b) the detected heartbeats errors, c) the reliabilities

Figure 6.28: K-means reliability result for jumping ECG signal. a) the original ECG, b) the detected heartbeats errors, c) the reliabilities

Figure 6.29: SAECC reliability result for arm moving ECG signal. a) the original ECG, b) the detected heartbeats errors, c) the reliabilities

The actual heart rate of walking ECG is 87.67, jumping ECG is 99.27, and of arm is 93.67, then for a 10 seconds window, there are 14-16 beats in it, and the K-means clustering method is applicable. In these ECG signals, there is no shape varying PQRST segments. From the graphs, we can see that the K-means added reliability method provides higher reliability scores compared to the SAECEG method in Figures 5.20, 5.22 and 5.23 and the reliability score still can correctly indicate the quality of the ECG segments.

6.7 Discussion

For ECG signals that contain shape varying PQRST segments, K-means added reliability method can effectively remedy the problem of accurate heartbeat estimates that exhibit low reliability. For normal ECG signals, K-means added reliability method is also applicable. The small increase on reliability values does not affect the signal quality assessment. WDIST distance measure with default denominator threshold $\tau = 0.25$ exhibits strong capability of being resilient to the effect of shape varying PQRST segments. Since SAECEG reliability is sensitive to the variation in PQRST shapes, it has the potential to be used to perform automatic PQRST morphology analysis.

Chapter 7

Chapter 7. Conclusions

7.1 Summary

In this thesis, two reliability evaluation algorithms and a heart rate estimation algorithm have been proposed. These three methods are all tested extensively with various datasets introduced in Chapter 3.

Our heart rate estimation algorithm was described in Chapter 4. This method pre-processes ECG signals first and then applies the CWT. The pre-processing includes band-pass filtering with the pass band from 0.1 to 50 Hz followed by baseline removal. CWT is calculated with scale 16, Haar wavelet. R peaks detection is performed on CWT coefficient line with a predetermined threshold. The proposed method was tested on various data. For standard MIT-BIH arrhythmia database, the sensitivity is 98.47% with a 99.61% positive predictive value.

In chapter 5, the SAEKG reliability evaluation method was given. The proposed method utilizes the R peaks positions to obtain PQRS segments. By comparing the PQRS segments to the SAEKG segment with PRD, CCORR and WDIST distance measures, PQRS segments are classified as being “good” or “bad”. The reliability is calculated from the proportion of bad PQRS segments which is given in Equation 5.6. Test results on various data show that SAEKG reliability evaluation is an effective

method to assess the accuracy of estimated heart rates. It can also be considered as a measure to assess quality of ECG signals. Linear regression analysis shows high correlation between the detection error and the reliability. Among three distance measures, WDIST has the best performance. This conclusion was based on the observation that WDIST had the highest cross-correlation coefficient in regression analysis. We also found that variations in PQRST shapes lower the SAEKG reliability values.

In Chapter 6, we presented the K-means added reliability evaluation method. K-means reliability was devised for remedying the problem with the ECGs containing shape varying PQRST segments. These have low SAEKG reliability values, in spite of accurate heart rate estimates. This method utilizes K-means clustering algorithm to classify PQRST segments to three clusters, then applies the distance measures. Our results show that K-means reliability method could be used on both shape varying PQRST ECG and normal ECG signals. It also increases the reliability of ECG data at low SNR range. Since WDIST is found to be resilient to the adverse effect of shape varying PQRSTs, it did not benefit much from K-means added method as PRD and CCORR. In Section 6.4.1, we discussed this feature of WDIST and verified it on various ECG data. Regression analysis also shows that PRD and CCORR have much bigger P2 difference between SAEKG and K-means method than WDIST.

We tested the proposed techniques on various ECG database, including standard MIT-BIH arrhythmia ECG database. Our conclusion is that the proposed heart rate estimation

method is fairly accurate, and the SAEKG and K-means reliability evaluation methods provide new ways to evaluate heart rate estimation results, as well as the quality of ECG signals. The proposed techniques in this thesis have following advantages: 1) they are simple and fast, and three reliability indices provide the evaluation results simultaneously; 2) they do not need any extra reference input and can handle any ECG data, or even other bio-signals; 3) with the reliability value in percentages in addition to three index values, small differences in ECG quality can be readily identified.

7.2 Future Work

A. Universal reliability values

We observed that PRD, CCORR and WDIST exhibit different performance on different types of noise. The reliability value does not correspond to a specific detection error, yet the ratio of reliability to detection error may give a hint on the type of noise. In practice, we have ECG signals recorded without noise type and SNR_{ECG} information. An investigation to determine universal reliability values based on noise type recognition would help to quantify the ECG signal quality level when applying reliability methods. A combination of the three measures could also be a better indicator for assessment of signal quality.

B. Adding global features

K-means added reliability method is able to mitigate the adverse PQRST shape varying effect. However, very low SNR_{ECG} ECG signal may still have high

reliability values than signals with higher SNR_{ECG} . Some global features can be obtained from ECG signals to amend the K-means method. Global features under consideration include permutation entropy, high-low frequency components ratio, and signal to baseband amplitude ratio.

C. Dynamic time window

It is known that our reliability method does not allow short time windows for SBD detection. However, test results show that short time windows may improve the accuracy of heart estimates. Considering the fact that heart rates usually do not exhibit a steep change, it is possible that a pre-HR estimation from single R-R interval may help to determine a proper time window for the whole ECG signal.

D. Real-time reliability evaluator

The proposed SAECG and K-means reliability evaluation methods are fairly fast. Any accurate QRS detector, which can provide the positions of R peaks can be used in conjunction with our reliability methods. With short delay, the reliability methods can provide real-time HR reliability reports, or ECG quality reports. It would be an invaluable tool for real-time ECG monitoring applications

E. Arrhythmia monitor

It has been noticed that with SAECG reliability method, WDIST has an obvious discrepancy from PRD and CCORR measures when ECG signal contains shape varying PQRST segments. It would be interesting to develop a monitor that can recognize when an arrhythmia occurs

F. Test methods under motion artifacts with ambulatory data

Monitoring ambulatory ECG is an important application. We will record more ambulatory data with different level motion artifacts for test.

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