Development of Noise-Tolerant Method for Arrhythmia Heartbeat Detection in Ambulatory Electrocardiogram

(携帯型心電計における不整脈心拍のノイズ耐性検出方法の開発)

By

Ziti Fariha binti Mohd Apandi

Graduate School of Engineering
Mie University, Japan

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A thesis submitted to the Division of Mechanical Engineering of the Graduate School of Engineering of Mie University in partial fulfillment of the requirements for the degree

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Advisor: Professor Dr. Ryojun Ikeura

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I dedicate this thesis to my parents, my husband and my children, Inara Aysha, Imran Ardani and Imaan Ayumi for their unconditional love and support.

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Abstract

Cardiovascular diseases have become one of the leading causes of mortality globally, and they are forecasted to remain so in the future. One of the common class of cardiovascular diseases is abnormal heart rhythms or arrhythmia. Some types of arrhythmias can be life-threatening, resulting in sudden cardiac death. The heartbeat classification is an approach to detect the arrhythmias in electrocardiogram (ECG) signal. One of the most important processes in heartbeat classification is the heartbeat detection or also known as QRS complex. However, detecting heartbeat is more challenging in an ambulatory ECG signal because the level of noise and artifacts produced during the daily life activities is higher compared to in a hospital setting. It is difficult to identify the QRS complex in the signal during high-intensity physical activities and low signal-to-noise-ratio, affecting the performance of heartbeat detection in the heart monitoring system. Therefore, it is necessary to develop a robust heartbeat detection method against the noise and artifact produced during daily-life activities. The aim of this study was to develop a noise-tolerant heartbeat detection method for heartbeat classification in order to detect the arrhythmias in ambulatory signals. To achieve that aim, three objectives were developed.

The first objective was to study and analyze the effects of noisy signal on the heartbeat detection performance. The relationship between the characteristics of the ECG noises produced in the ambulatory ECG signals recorded during daily life activities and the heartbeat detection performance was investigated. For this purpose, three well-known algorithms to detect the heartbeat were employed. The detection algorithms were evaluated using two types of ambulatory datasets: the ECG signal from MIT-BIH Arrhythmia database and the ECG-noise simulated signals with different intensity of baseline wander, muscle artifact and electrode motion artifact. The findings showed that the signals contaminated with noise decreased the potential of heartbeat detection in ambulatory signal, with the poorest performance coming from the electrode motion artifact. In conclusion, none of the algorithms was able to detect all QRS complex without any false detection at the highest level of noise. The electrode motion artifact influenced the heartbeat detection performance the most compared to the muscle artifact and

baseline wander, showing the highest number of misdetections and false detections.

The second objective was to propose and develop a robust and noise-tolerant heartbeat detection method. For this purpose, the threshold-based heartbeat detection was developed. To improve the performance of the detection method, the Savitzky-Golay moving average and autocorrelation technique were used to reduce false detections in this study. The proposed method consisted of processing and QRS detection stages using six techniques, including band-pass filter, derivative, squared, Savitzky-Golay moving average, autocorrelation and adaptive threshold. The Savitzky-Golay moving average was used to smoothen the signal data and autocorrelation was used to generate the period of the heartbeat and to refine the candidate QRS complex. The proposed method was evaluated using three different datasets, including the real data during walking and running on the treadmill. Based on the results, the proposed method performed well despite its use in different noisy conditions. Based on the results, it could be concluded that the proposed method had a good performance, especially in electrode motion artifact.

Finally, the arrhythmia detection system was developed by using the heartbeat classification approach to achieve the third objective. The heartbeat classification approach consisted of four stages: ECG signal processing, heartbeat segmentation, feature extraction and classification. The proposed noise-tolerant heartbeat detection method was adopted and the set of features that represented each heartbeat was extracted for the classification. Fourteen features were extracted separately to represent each heartbeat, with seven features of heartbeat interval and seven features of ECG morphology. After evaluating the classification algorithms, the k-NN algorithm was used to construct the classification model and as tests in the experiments. Based on the results, the proposed heartbeat classification performed better when classifying normal and ventricular beats, except the supraventricular beats. In the noisy ECG signal, the classification method also performed better than using pan Tompkins algorithm as the heartbeat detection.

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List of Abbreviations

ECG	Electrocardiogram
SVA	Supraventricular
VT	Ventricular Tachycardia
VF	Ventricular Fibrillation
PVC	Premature Ventricular Contraction
SGMA	Savitzky-Golay Moving Average
ACF	Autocorrelation Function
MIT-BIH	MIT-BIH Arrhythmia
MIT-NST	MIT-BIH Noise Stress Test
GUDB	Glasgow University Database
Hz	Hertz
KPH	Kilometers per Hour
dB	Decibels
SNR	Signal-Noise-to-Ratio
SE	Sensitivity
PP	Positive Predictivity
ACC	Accuracy
DER	Error Detection
k-NN	k-Nearest Neighbors
SVM	Support Vector Machine
LD	Linear Discriminant
DT	Decision Tree
ANN	Artificial Neural Networks
NN	Neural Network
HMM	Hidden Markov Model
DWT	Discrete Wavelet Transform
CWT	Continuous Wavelet Transform
PCA	Principal Component Analysis
ICA	Independent Component Analysis

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Chapter 1
Introduction

1.1. Research Motivation

Cardiovascular diseases (CVD) have become one of the leading causes of the current mortality globally and it is forecasted to occupy the same ranking up to 2030 [1]. As reported by the World Health Organization, CVD accounted for an estimated of 17.9 million deaths every year because of the CVD, representing 31% of all global deaths [1]. The majority of deaths from CVD are caused by sudden cardiac death (SCD), referring to an unexpected death or arrest caused by loss of heart function [2]. It has been reported that one of the causes of SCD is arrhythmia, a condition in which a patient heart beats irregularly in the electrocardiogram (ECG) signal [2]. About 80% of the sudden cardiac death is the result of ventricular arrhythmias [2]. According to prior studies [2-3], many cases of SCD occur outside of the hospital environment, during daily life activities and approximately 70% of all cardiac and breathing emergencies happen at home. The prediction of SCD has been studied, and improving the methodologies to detect arrhythmias in ECG signal in order to prevent SCD during daily life activities has become important challenges for the modern cardiology [3-4].

The classification of heartbeats approach has been used in order to identify and detect the arrhythmias in ECG signal [4-7]. One of the first important steps for classifying the heartbeats is the identification of the QRS wave also known as the QRS complex, heartbeat detection or beat detection [5]. The QRS complex is the prominent feature in the structure of ECG signals and it can be used to identify abnormalities in the heartbeat. Moreover, the performance of QRS detection affects the accuracy of heartbeat classification [4, 8]. Hence, numerous studies have been conducted to improve the detection of QRS complex, and different algorithms have been proposed and developed for this process [8-13]. Existing methods were tested on noise-free, carefully chosen, and often clean ECG signals to evaluate and produce high accuracy results assumed to reflect the overall performance of detectors. However, the existing methods may not produce the same performance and accuracy in the ambulatory ECG signal, especially with the presence of a noisy signal, since the level of artifacts produced is greater than the monitoring process in the hospital setting.

Unlike standard ECG, ambulatory ECG records the signal continuously over a long period in an out-of-hospital setting using a conventional Holter monitor [5, 14] or other wearable devices [15-16] when performing daily life activities, such as resting, housework, exercise, and other physical works. Various types of noise from stationary and non-stationary sources may occur simultaneously in an unpredictable manner. Furthermore, the noise can also distort the features of the signal [16-19]. This is important in heartbeat detection as it may lead to the false detection of arrhythmias. As a result, the process of acquiring an accurate and reliable measurement of heartbeats in the arrhythmia detection system can also be affected.

Therefore, it is vital to determine the best method of heartbeat detection in noisy signals to develop an accurate arrhythmia detection system that is robust against the noise and suitable for ambulatory monitoring. This thesis investigated the effects of noise with various intensity levels on ambulatory ECG signal and the performance of QRS detection. The thesis focused on improving existing methodologies to propose a robust heartbeat detection in the noisy signal before developing an arrhythmia detection system using the classification approach for ambulatory ECG signal.

This study was significant because it addresses one of the main problems in the field of ECG signal analysis and ambulatory monitoring. This study also provides an important understanding of the effects of intensity levels of noise from the ambulatory environment on the performance of heartbeat detection in the ECG signal. Considering that the robust heartbeat detection method plays an important role in the development of arrhythmia detection, the findings will make a critical contribution to the development of the ambulatory heart monitoring system.

1.2. Research Background

As this thesis is entirely focused on the analysis of the ambulatory ECG signal, a brief description and basic concepts of this study are included. The following sections cover the description of the basic structure of the ECG signal as a result of the connected electrical conduction system that leads to heart activity. Then, a general overview of the abnormalities in ECG signal that cause the arrhythmias is provided. More specifically, the introduction of ambulatory ECG and the comparison with standard ECG are described, leading to the explanation of noises and artifacts in ambulatory ECG.

1.2.1. Basic Structure of Electrocardiogram

The electrical conduction system of the heart, shown in Figure 1.1 allows for the generation and propagation of impulses via a specialized conduction pathway, which stimulates the heart to contract and pumps blood [20-21]. When the heart muscle contracts and pumps the blood for all parts of the body, action potentials will be released through the mechanical process within the heart muscle, leading to electrical activity. This electrical activity signal can be acquired by means of electrodes positioned on the subject's thorax and then amplified, and recorded by the electrocardiograph.

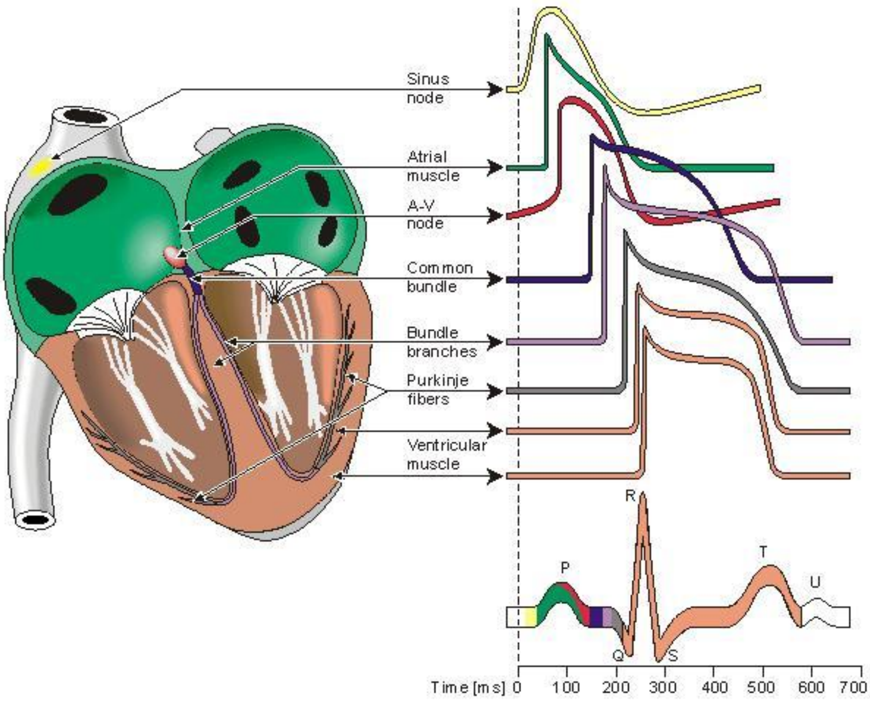


Figure 1.1. The heart conduction system with its main components and their typical potential waveforms on surface ECG [21].

Electrocardiography is a commonly used, noninvasive procedure for recording heart electrical activity. The recorded signal, named Electrocardiogram (ECG), graphically shows the series of waves associated with electrical phenomena of depolarization and repolarization of the heart during the cardiac cycle. As can be seen in Figure 1.1 [21], the structure of the ECG signal represents the electrical conduction of the heart activity. As it is a non-invasive, rapid and cost-effective test, ECG is a valuable and highly versatile tool in clinical practice for detecting several heart dysfunctions by inspecting the alterations in the ECG pattern shape or duration of wave intervals [21].

Each phase of the depolarization and repolarization process is reflected on ECG [20]. The ECG signal begins with the atrial depolarization that creates the P wave, which is followed by the QRS complex and the T wave as shown in Figure 1.2. Each wave is generated by a physiological event of the heart where the P wave reflects the depolarization of the atria muscle; it has a duration of 0.08–0.11 second in a healthy heart. The Q, R, and S points represent the QRS complex derived from the depolarization of the ventricular muscle with a normal duration of 0.06–0.10 second. The T wave indicates the repolarization of the ventricular muscle that normally has a duration of 0.20 second [20]. The most recognizable point in the ECG signal is the R-peak, which has the highest amplitude. The other waves in the QRS complex, namely Q and S, might not always be separated in the ECG. The QRS complex and R-peak play an essential role in many algorithms used to automate ECG analyses [8, 13]. Based on the identified QRS complex and R-wave, the rest of the waves and ECG features can be detected. The main features of an ECG signal and their origin are visualized in Figure 1.3 [22] and summarized in Table 1.1.

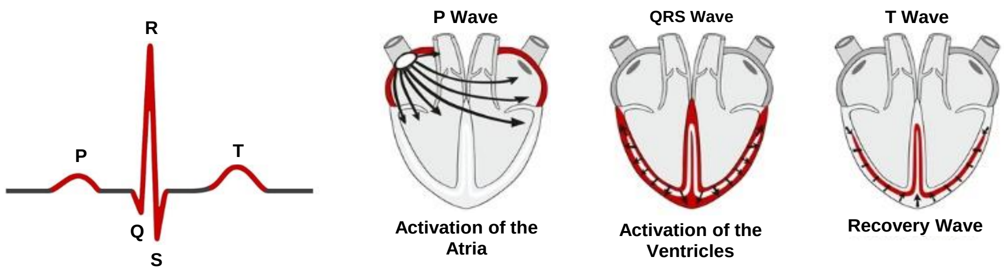


Figure 1.2. The depolarization and repolarization process reflected on ECG. [https://www.carolinaheartandleg.com/arrhythmia/arrhythmia-2/]

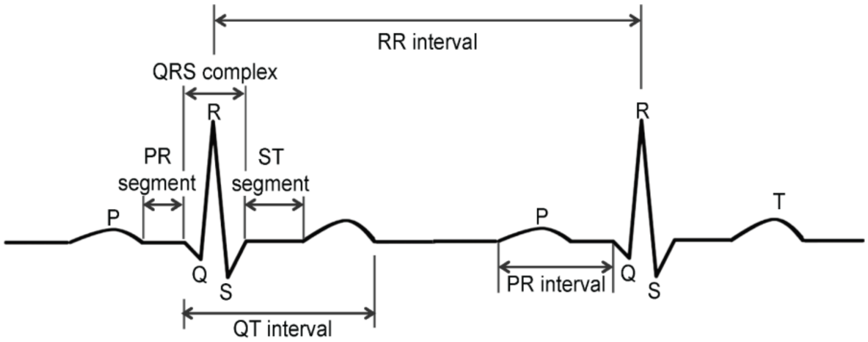


Figure 1.3. Main features in ECG signal [22].

Table 1.1. The main structure of an ECG signal and its origin.

Type	Name	Electrical Activity
Wave	P	Atria depolarization
	Q	Depolarization of the interventricular septum area between the ventricles
	R	Depolarization of the main mass of the ventricles
	S	Final depolarization of the ventricles, up the outer walls
	T	Ventricular repolarization
	U	Late ventricular repolarization
Section	QRS Complex	Ventricular depolarization
	PR Interval	Time between the onset of atrial and onset of ventricular contraction
	QT Interval	Ventricular depolarization and repolarization
	RR Interval	Time between consecutive R wave provided to heart rate measure
	PR Segment	Time delay between atrial and ventricular activation
	ST Segment	Plateau phase of ventricular depolarization

1.2.2. Arrhythmias in ECG Signal

Arrhythmias, also known as cardiac arrhythmias are defined as abnormal changes in the heart rate due to improper heart beating, causing failure in the blood pumping. Some arrhythmias have no symptoms while others are dramatically debilitating, such as palpitations or skipped beats, dizziness, fatigue, light-headedness, fainting and possibly even leading to life-threatening conditions. Cardiologists use ECG to detect arrhythmias in the heart when the electrical activity of any group conditions is irregular [5]. The ECG is essentially a non-stationary signal where the arrhythmia may occur at random in the time-scale.

In ECG signal, normal heartbeat or normal sinus rhythm is characterized by a regular cardiac rate with normal QRS complexes (Figure 1.4). The P-wave is normal in shape and synchronized with the QRS complexes. The heart beats regularly at a rate of 60 to 100 beats per minute (bpm). The abnormal heartbeats are characterized by irregular cardiac rate with dynamic QRS complex that can either be too slow or too fast, called bradycardia and tachycardia, respectively. Tachycardia refers to a fast resting heart rate, usually over 100 beats per minute while bradycardia refers to slow resting heart rate, less than 60 beats per minute. Under certain circumstances, the presence of these heart rates is considered normal. During an exercise or stress, it is normal to develop a fast heartbeat and during sleep or deep relaxation, it is not unusual for the heartbeat to be slower.

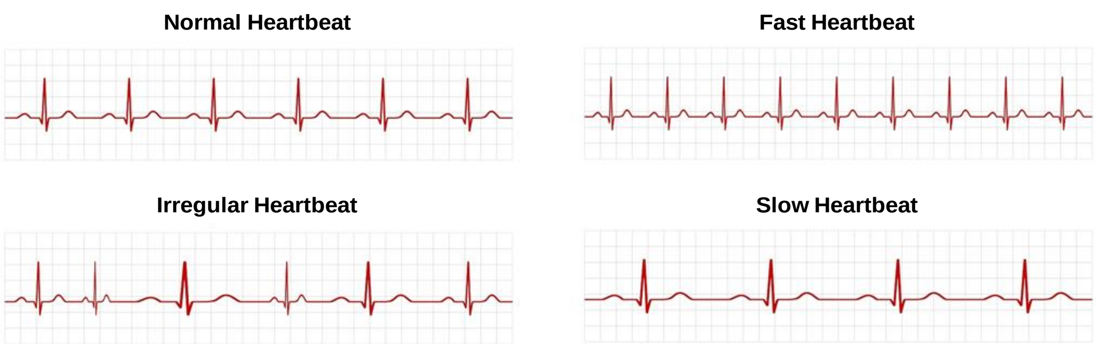
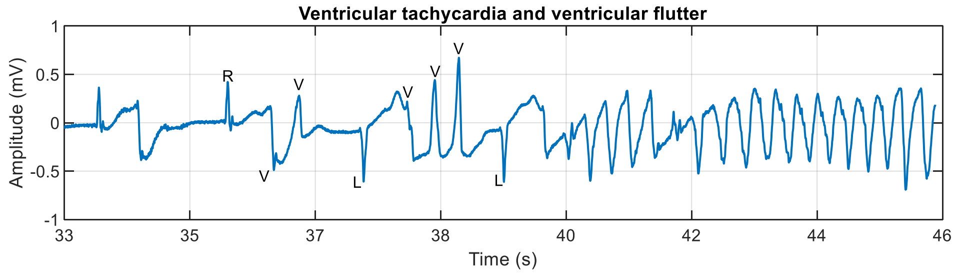


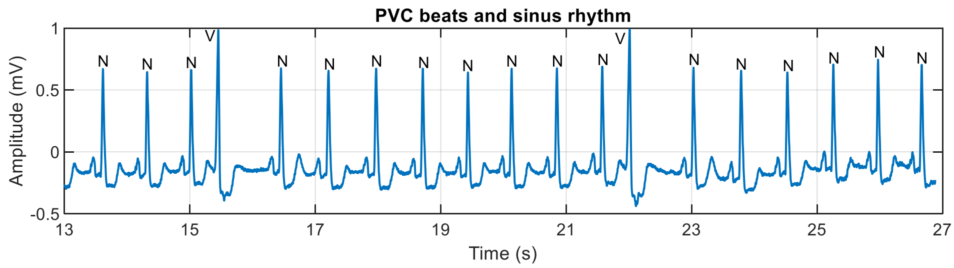
Figure 1.4. Normal and abnormal heartbeat.
[https://www.carolinaheartandleg.com/arrhythmia/arrhythmia-2/]

There are several types of arrhythmias and each type has a pattern in ECG. Generally, arrhythmias are divided into two categories: ventricular and supraventricular [23]. Ventricular arrhythmias occur in the lower chambers of the heart, namely, the ventricles. Supraventricular arrhythmias (SVA) are heart rhythm disorders affecting the upper part of the heart, that is the atria or the atrial conduction pathways [20]. The most common arrhythmia correlated with sudden cardiac death is the ventricular tachyarrhythmia such as ventricular tachycardia (VT) or fibrillation (VF). Ventricular tachycardia might be followed by a ventricular flutter that can turn into ventricular fibrillation, which is a very dangerous condition [23].

An example of an ECG signal that begins with VT and then progresses into ventricular flutter is given in Figure 1.5 in which the flutter wave is substantially different from the sinus rhythm. Both of the signals include premature beats that arise from ventricles called premature ventricular contraction (PVC), which is marked by V, normal beats marked by N, right bundle branch block beat marked by R, and left bundle branch block beat marked by L.



(a)



(b)

Figure 1.5. Ventricular tachycardia changing to ventricular flutter in the ECG recording 207 from MIT-DB (a) is compared to sinus rhythm that contains two PVCs in MIT-DB record 105 (b).

1.2.3. Ambulatory ECG Monitoring

The ECG is typically recorded using a conventional standard 12-lead ECG device, with ten electrodes being worn on the chest surface and the limbs while the patient is in a resting position in a clinical environment [5, 14, 17]. The 12-lead ECG is mostly intended for short-term monitoring and it has been used as a standard signal to diagnose arrhythmia

[5, 14]. For long-term ECG monitoring, the ambulatory ECG is most frequently utilized. Ambulatory ECG can be recorded using a conventional Holter monitor introduced by Norman J. Holter [24]. Holter monitor is a small portable ECG machine that is used typically for 24 to 48 hours. It is worn around the patient waist and 3 to 5 electrodes need to be taped on the patient chest skin as shown in Figure 1.6. In contrast to the standard ECG, the ambulatory ECG records the signal continuously for a long period of time during daily life activities, such as resting, doing housework, performing exercises and other physical activities. Since Holter monitor has produced a good quality ambulatory ECG, it has been a standard signal for monitoring patients outside of hospitals.

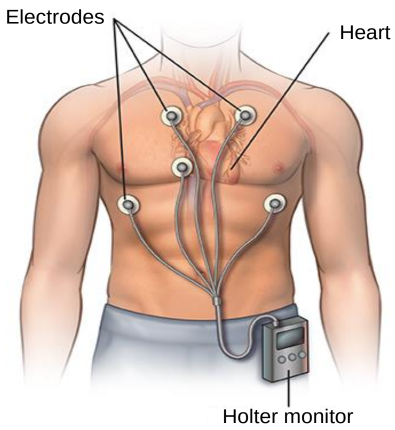


Figure 1.6. Example of Holter monitor.
https://www.mountnittany.org/articles/healthsheets/7176

The ambulatory ECG monitoring can reveal heart conditions that would not be found during an ECG measurement in the hospital since some heart problems occur only rarely or during certain activities. Consequently, the utilization of heart monitoring devices for daily application has become important. Recent technology advancement is capable of increasing the use of wearable devices for heart monitoring, such as a smartwatch, smart clothing, fitness tracker, mobile cardiac application, body sensor patches and others [15-16, 25]. The wearable devices can record ambulatory ECG signals and allow greater monitoring of patient mobility than the Holter monitor [15-16, 25]. Even though the devices have high mobility, they also have limitations, producing low signal quality for medical use. Furthermore, they have a limited duration of recordings depending on their technologies.

Although ambulatory ECG is very useful for heart monitoring, the body movement activities like walking, climbing stairs, jogging, running, exercising and other high-intensity level activities have posed a challenge for collecting a good quality ambulatory ECG. These conditions may produce the noises and artifact that will overlap the ECG signal and distort its quality. Consequently, the clinical and morphological pattern of the ECG signal such as QRS complex is interfered, affecting the heart monitoring process. Figure 1.7 shows the comparison between a clean ambulatory signal and a noisy signal. As can be seen, it is difficult to determine the morphology of ECG in the noisy signal due to the low-quality compared to the clean signal.

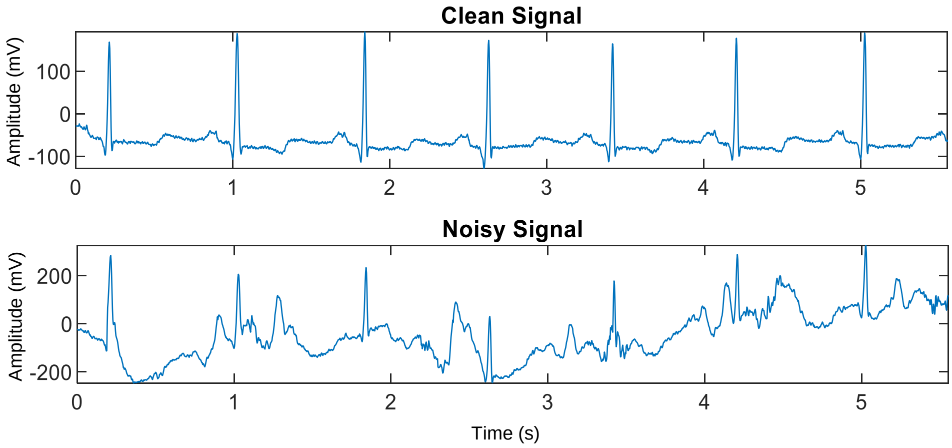


Figure 1.7. Comparison clean and noisy ambulatory ECG signal.

1.2.4. ECG Artifacts and Noise

In ambulatory ECG, various types of noises and artifacts may occur simultaneously and unpredictably originating from stationary and non-stationary sources [14, 17, 19]. These noises could emerge due to physiological and non-physiological factors, such as muscle activity, skin movements, electrical devices or improper use of the equipment [13, 19]. Noises from different sources have different typical characteristics, such as frequency spectrum and amplitude. Among them, baseline wander (BW), muscle artifact (MA) and electrode motion artifact (EM) have frequency range within the frequency limit of ECG signal, possibly manifesting similar morphology as the ECG signal and distorting the clinical features of the signal, which is important in recognizing arrhythmias [19, 26].

The amplitude and frequency of ECG signals as affected by these noises in comparison to clean ECG are presented in Figure 1.8. The BW and abrupt drift as shown in Figure 1.8 (a) could be due to the subject's respiration movements and the loose or dry electrode-skin contact [19, 27]. The BW amplitudes depend on several factors, such as the subject movements, properties of electrode, and skin impedance [19, 27]. In general, the frequency of the BW is below 1 Hz but through exercise activity, the frequency of the BW in ECG recording may increase with the increasing rate of breathing. The MA or electromyogram as shown in Figure 1.8 (b) is produced during a sudden body movement by the electrical activity of muscles [19]. Usually, the frequency of MA noise ranges from 20 and 1000 Hz which can cause challenges in eliminating MA without interfering with the clinical features of the ECG signal. The EM artifacts and the induced impedance change as shown in Figure 1.8 (c) are caused by the electrode motion, and they have similar frequency components as the ECG signal, ranging from 1 Hz to 15 Hz [28]. Major EM artifact can distort the signal, leading to incorrect QRS complex and the wrong diagnosis of arrhythmias.

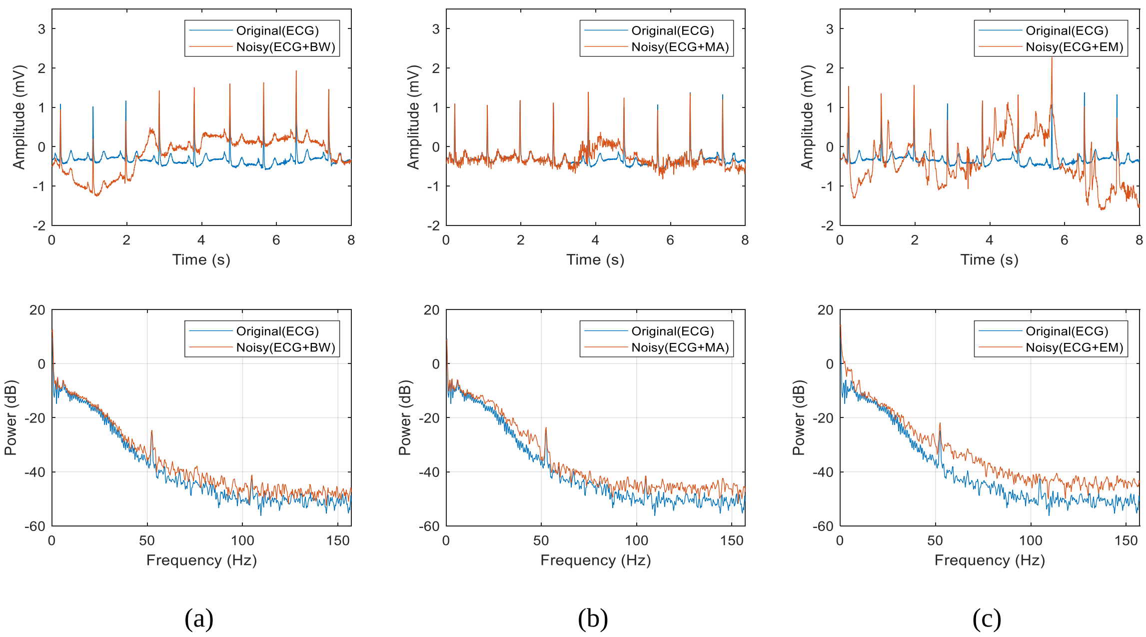


Figure 1.8. Eight-second clean and noisy ECG signals at a sampling rate of 360 Hz: (a) ECG with BW; (b) ECG with MA; (c) ECG with EM artifact.

The noises may appear as morphologically similar to the ECG signals, distorting the QRS complex and clinical features of the signal, especially when contaminated with MA and EM. It is worse when the patient performs high-intensity physical activities, such as jogging and running. A poor ECG signal quality may result; thus, it will be difficult to identify the QRS complex within the ECG signal. The high noise or artifacts can make the signal virtually unreadable, hide small amplitude variations in the ECG or lead to wrong diagnoses. This difficulty will increase misdetections and false detections of the QRS complex as visualized in Figure 1.9. Hence, it is necessary to investigate the effects of ECG artifact and noise generated in ambulatory ECG signal and to reduce the disturbances from the signals in order to use the signal for detection of arrhythmias.

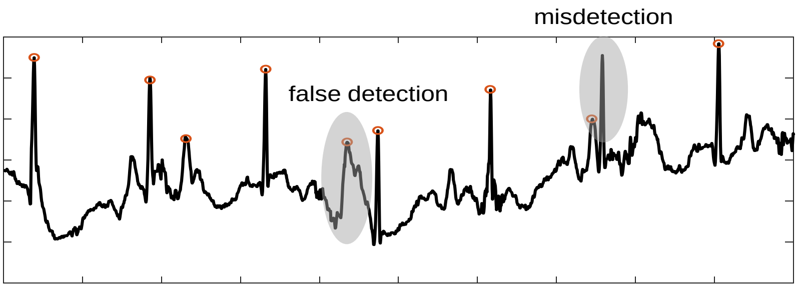


Figure 1.9. False detection and misdetection problem of QRS detection.

1.3. Research Problems

Many studies have been carried out to develop ECG heartbeat classification system and improve the performance of detecting arrhythmias. Most of the studies in the heartbeat classification system have focused on feature extraction [6-7, 29-30, 31, 32] and classification method [33-39] in order to improve the detection performance. While some researchers have studied the pre-processing and detection of QRS method [8-9], too little attention has been put to relate these methods with the arrhythmias heartbeat classification system.

According to a study [5], one of the important issues of ambulatory ECG is the inconsistent signal quality due to noise and artifact induced in daily life activities. It has also been reported that this issue would impact the QRS detection and classification results [40]. However, this issue was not yet considered in some previous studies of heartbeat classification system although they used the ambulatory ECG signal data in their works [6-7, 30-31, 33-34]. Several attempts have been made in the recent works in which the false alarm reduction and signal quality classification have been proposed in the heartbeat classification system to address this issue [41]. Nevertheless, these studies have not taken pre-processing and QRS detection into consideration. In addition to that, the studies [5, 40] have reported that the techniques employed during the pre-processing steps and detection of QRS directly influenced the final classification results. Thus, in this study, we intended to focus on the pre-processing and QRS detection process in arrhythmia heartbeat classification system in order to address the issues in ambulatory ECG signal and improve the classification results.

In the literature, most of studies in the heartbeat classification system preferred to use conventional heartbeat detection method in their work [5-7, 30, 32, 38-39, 41]. The threshold-based heartbeat detection method has been used to detect the QRS in most of the works [6, 32, 38-39]. This method has drawn significant attention because of its simplicity, computational efficiency, and suitability for ambulatory devices [29]. However, the threshold-based detection method is quite sensitive to the noise, and their performance is affected in the low quality signal [9-11, 29]. Therefore, in this study, we focused on the threshold-based detection method and examined the technique that can be used to improve the detection performance in noisy ECG signal.

Some of the studies have taken into account the influence of noise from the ambulatory environment [13, 42-43]. Nevertheless, the details on the specific noise types and the level of noise intensity that affect the QRS detection performance are still unclear. It is unknown what kind of noise from the ambulatory environment that most affects the detection of QRS performance [43]. Therefore, we investigated the effects of noise on the QRS detection, and the characteristics of noises that could distort the ECG signal morphology. In this study, we compared the performance of previous threshold-based method under different noise conditions to analyse the effects of noise on QRS detection.

On the other hand, researchers have suggested many noise reduction methods to address noisy signal and detect QRS complexes [44-47]. Many works have filtered the signal first to increase the robustness [9-10, 47]. Nonetheless, filtering does not work for EM and MA noises. According to a study [48], periodical property of ECG is able to improve the QRS detection in ECG signal with motion artifacts. Thus, autocorrelation has been investigated in this study. In the previous work [44], the short autocorrelation with template matching has been proposed for noisy ECG signals. However, the template matching was computationally expensive because of the sample-by-sample moving comparison with the template along the ECG signals.

Therefore, in this study, the noise-tolerant heartbeat detection method was proposed. The proposed method modified the Pan Tompkins algorithm by using the autocorrelation technique to improve the detection in noisy signal. In contrast to a previous study [44] that used template matching in their work, the threshold-based detection method was employed as the last stage in this study. However, the autocorrelation could produce an error estimation of the periodic peak when dealing with high noise due to higher noise spikes in the signal. To deal with this issue, the Savitzky-Golay moving average (SGMA) technique [49] was used to smooth the signal, thus improving the performance of autocorrelation.

1.4. Objective

This thesis aims to study the methodologies to improve the detection of arrhythmias during daily life activities, especially during the performance of high-intensity physical movement activities. In order to achieve that, this study focused on the most important step in the detection performance of arrhythmia: the detection of the QRS complex, also known as heartbeat detection. Hence, three objectives were developed as follows:

1) To study and analyze the effects of noisy signals on heartbeat detection performance for ambulatory arrhythmia monitoring. Under this objective, the relationship between the characteristics of ECG noises produced in the ambulatory ECG signal recorded during daily life activities and heartbeat detection performance is investigated.

2) To propose a noise-tolerant QRS detection method that can improve the detection performance for a noisy signal. For this purpose, the Savitzky-Golay Moving Average (SGMA) technique and autocorrelation technique are used to develop the QRS detection method. The performance of the proposed method in a noisy ECG signal is then evaluated.

3) To develop the arrhythmia detection system for ambulatory ECG signal using the heartbeat classification approach. For this purpose, the proposed QRS detection together with feature extraction and classification algorithm are implemented to

develop the heartbeat classification model. Finally, the final performance of the heartbeat classifier is evaluated.

1.5. Outline of Thesis

This chapter provided the motivation of this study and outlined the brief background including the basic structure of ECG, arrhythmias on ECG signal, ambulatory ECG monitoring, and ECG artifacts and noise in ambulatory ECG. The chapter also presented the objectives, problems, and challenges of the research work in this thesis.

The rest of the thesis is organized as follows:

Chapter 2 includes the literature review of the QRS detection method and the approach of arrhythmia detection, including the heartbeat classification method.

Chapter 3 contains the description of the experiment data and the methodology carried out in this study. It also elaborates the experiment conducted in this thesis. Besides that, the evaluation metrics used in the validation of QRS and arrhythmia detection are also provided in this chapter.

Chapter 4 presents the experiment on the effects of noise and artifacts in ambulatory ECG signals on heartbeat detection performance. For this purpose, the relationship between heartbeat detection and characteristics of noises under different noise conditions is investigated. Besides that, the comparison of the performance of heartbeat detection on various noise intensity levels is analyzed and presented in this chapter.

Chapter 5 includes the development of the proposed noise-tolerant QRS detection algorithm. For this purpose, the band-pass filter, derivative, squared, Savitzky-Golay moving average smoothing, autocorrelation, and adaptive threshold have been implemented to identify the QRS complex. In this chapter, the performance of the proposed QRS detection method is also evaluated and presented.

Chapter 6 outlines the implementation of the heartbeat classification approach with the proposed heartbeat detection algorithm to detect arrhythmias. For this purpose, the QRS detection is identified using the proposed heartbeat detection method before the selection features are extracted. Then, the classification model is developed to classify heartbeat in the ambulatory ECG signal. Based on the classification model, the arrhythmias are identified. The performance of arrhythmia detection is validated and presented in this paper.

Finally, **Chapter 7** provides the concluding remarks on the work carried out in this thesis, limitations of this study, and future directions for this research.

Chapter 2
Literature Review

2.1. Review on Heartbeat Detection Method

Many previous studies have been conducted, and different algorithms have been proposed to develop heartbeat detection method in order to improve the detection of QRS. The difficulties to improve the detection of QRS arise mainly because of the diversity of the QRS waveform, abnormalities, low SNR as well as artifacts accompanying the ECG signals [29]. Elgendi et al. [29] investigated the existing QRS detection methodologies that can be used for portable, wearable, battery-operated, and wireless ECG systems. This previous study compared the different QRS enhancement and detection techniques based on three assessment criteria: (1) robustness to noise, (2) parameter choice, and (3) numerical efficiency. Based on the review, most of the heartbeat detection method used in previous studies can be categorized into threshold-based, neural networks, hidden markov model, and matched filter.

Threshold-based

The threshold-based method has been used in the literature as the last stage for most QRS detection algorithms. Pan and Tompkins [9] developed a QRS method based on slope, amplitude and two sets of thresholds. This method becomes a standard and it has been studied in the R-peak detection field. The work in a study [50] optimized the decision rules in [9] by performing test of three estimators for the adaptive threshold placing. The alteration for the threshold-based method was carried out in the pre-processing stage in a study [10], by proposing rectifying process instead of squaring the signal as done previously [9]. Zong et al. [51] used the curve length transformation via a nonlinear scaling factor to enhance the signal before applying an adaptive threshold in the decision rules to determine the QRS. Another technique by Elgendi [52] used the block of interests from the moving average signal to create the threshold. The author claimed that by using the block of interests to locate the R-peak, the detection accuracy was increased in a low

SNR. Another threshold-based method in previous studies used different approaches of pre-processing or threshold calculation, such as RS slope algorithm [53], finite state machine algorithm [54], sixth power algorithm [55], and Hilbert transform [42]. According to a study [29], the threshold-based method was considered computationally efficient compared to other methods, and was suitable for ambulatory devices. However, the performance of threshold-based method was affected by low SNR and sensitivity to noise.

Neural Network

With the popularization of machine learning and large data, the neural network (NN) algorithm was used to detect the QRS complex in a previous work. Yu et al. [56] developed the QRS detection by using wavelet transform and NN. Xue et al. [57] suggested the neural network-based adaptive matching filter method and achieved high accuracy. However, due to the large amount of computation and large occupation of space, it was not widely considered [52]. According to Clifford et al. [58], NN was highly sensitive to noise.

Hidden Markov Model

Hidden markov model (HMM) is another method used in previous studies to detect the QRS complex. In a study [59], HMM was used only with a band-pass filter to detect the QRS. Krimi et al. [60] developed the combination of wavelet transform and HMM for segmenting the heartbeat. However, according to a study [51], HMM was sensitive to noise, baseline wander and heart rate variations. The number of parameters that needs to be set in an HMM is large, with usually 15 to 50 parameters that need to be evaluated [59-60].

Matched Filter

Kaplan [61] has suggested the matched filter method for QRS detection. Ruha et al. [62] used practical matching filter with 15–40 Hz band-pass filter to detect QRS wave for a better SNR. Nakai et al. [44] developed the template matching technique based on the matched filter for low SNR applications. In a more advanced method, Nguyen et al. [45] suggested triangle template matching to reduce the complexity in the detection of QRS. However, according to a study [46], matched filters are computationally expensive because of the sample-by-sample moving comparison with the template along with the ECG signals.

Based on the review, various techniques have been developed to detect the QRS complex. However, most of the studies used standard clean data for the evaluation and assumed to reflect the overall performance of detectors. Friesen et al. [13] have investigated the noise sensitivities in nine different QRS detection algorithms that evaluated a normal, single-channel lead, synthesized ECG database corrupted with five different types of synthesized noise. Usually, the de-noising of ECG signal requires a band-pass filter while reasonably preserving the clinical features of ECG signals (P, QRS, and T waves) at the same time. Perhaps, a more sophisticated algorithm may filter the ECG more effectively.

Sameni et al. [47] proposed a Bayesian framework that filtered the ECG better than the conventional band-pass filtering, adaptive filtering [63], and wavelet de-noising [43,60] over different types of noise using highly realistic synthetic ECG. Sharma et al. [64] proposed a wavelet-based de-noising method tested on real ECG data and synthetic ECG signals. However, both algorithms are numerically inefficient.

In previous studies, autocorrelation has been used for improving noise-tolerance [44, 65-66] in ECG signal. Nakai et al. [44] developed short-time autocorrelation with template matching approach to noisy ECG signals. The autocorrelation techniques have been used in non-invasive monitoring [65] to detect the heart sounds in low SNR [66]. According to a study [66], it was effectively used to detect the primary heart sounds in noisy phonocardiogram signals. It is also useful to find the period of continuous signals and to identify the present components by cross-correlating a signal with itself. By using the similarity of the waveforms, it can automatically suppress the periodic noise in the signals.

2.2. Review on Heartbeat Classification for Arrhythmia Detection

Many studies have been carried out to develop the ECG heartbeat classification system and to improve the performance of detecting arrhythmias. Most of the studies in the heartbeat classification system have focused on feature extraction and classification method; other researchers have studied the pre-processing and detection of heartbeat in order to improve the detection performance.

Pre-processing Methods

Most of the studies in heartbeat classification system have used digital filter technique to process the ECG signal [9-11]. These methods work well to attenuate known frequency bands, such as the power line interference with 50Hz to 60Hz since they allow quick and easy application of the reject band filter. In a study [6], De Ghazal et al. used two median filters to remove the baseline wander in the ECG signal. The same pre-processing also has been used in another study [34]. However, researchers also used different techniques for pre-processing. In a study [63], adaptive filters were proposed for the noise removal in ECG signal. Xue et al. [57] surmounted some of these difficulties by using adaptive filters based on neural networks such that the noise reduction was significantly improved. According to Thankor and Zhu [67], this technique has a constraint and it does not offer great advantages over the digital filters. Ye et al. [68] used a wavelet-based approach to remove baseline wander and then applied a band-pass filter at 0.5-12 Hz to maximize QRS complex energy. Bazi et al. [69] proposed the use of high-pass filter for noise artifacts and a notch filter for power network noise.

Heartbeat detection Methods

The heartbeat detection methods have been reviewed in the previous section. However, in view of heartbeat classification system, the method most widely used in the previous work is the threshold-based method [6, 32, 38-39]. Based on the review, the Pan Tompkins algorithm [9] has been used in most previous works of heartbeat classification systems. More sophisticated methods have also been used, such as methods based on neural networks [43,57-58], wavelet transform [43, 60], and others.

Feature Extraction Methods

Many researchers have used time domain and frequency domain in their work to improve the classification results [6-7, 30-31, 70]. Based on the review, the most common feature found in the literature was from the heartbeat interval also known as RR interval. According to a study [6], the RR interval has a great capacity to discriminate the types of heartbeats. Lin and Yang [31] showed that the use of a normalized RR interval significantly improved the classification results. Only normalized RR intervals were used in that work, and the results were comparable to the state-of-the-art methods. Doquire et al. [71] confirmed the efficiency of normalized RR intervals by means of feature selection techniques. Other features extracted from the heartbeat intervals are the QRS interval or the duration of the QRS complex. Some types of arrhythmias provoke variations in the QRS interval, making it a good discriminating feature [6-7]. Other researchers used wavelet transform method to extract the features [12, 71-72]. The discrete wavelet transform (DWT) [12] and continuous wavelet transform (CWT) [71] have become the most used wavelet techniques in the previous studies. However, according to a study [72], the choice of the mother wavelet function used for feature extraction is crucial to construct the classification model.

Classification Methods

Previous studies have reported the performance of classification algorithms in order to improve the classification results. The classification algorithms that have been used in previous studies include support vector machine (SVM), linear discriminant, k-Nearest Neighbor, artificial neural networks and logistic regression [6, 30, 36-37, 41, 67]. Park et al. [36] used SVM and validated the method according to AAMI standards and the scheme proposed by de Chazal et al. [6]. De Lannoy et al. [37] managed to overcome the imbalance of the database with SVM by alternating the objective function for each class by using weighted SVM. De Ghazal et al. [6] proposed the linear discriminants a statistic method based on the discriminant functions and it has been used as the classifiers in their work. The authors claimed that the classifier was chosen for its simplicity, and for the fact that they did not want to emphasize the classifier, and instead, they used the proposed features to improve the classification results [6]. Another classification technique used in the previous work is k-NN. Mishra and Raghav [73] used a classifier based on k-NN and reported promising results. However, the computational cost was not mentioned in their work. Tanatorg et al. [41] also used k-NN and compared with other learning classifications. The study showed that k-NN emphasized the performance of learning model, especially in noisy data. However, they only evaluated two class of beats in the ECG signal, deviating from the recommendations of AAMI.

Researchers have raised several problems related to the evaluation of the classification of cardiac arrhythmias [5-7]. Results presented in the literature usually used the extremely unbalanced MIT-BIH database. However, this aspect has been ignored by many authors in their work. As such, numerous proposed methods do not follow a fair evaluation protocol. Several authors used the same data for training and testing the evaluation, and intended to achieve higher accurate method. Luz and Menotti [74] investigated some models [32, 38-39] that presented an overall accuracy of nearly 100% and that were not concerned about the heartbeat selection scheme. Afterwards, they re-evaluated the results produced by the methods with the objective of reporting the experiments in accordance to the protocol recommended by AAMI using the division scheme proposed in a study [6]. Although some works in the literature strongly drew attention to this bias problem, few authors have taken the precautions of following a protocol as proposed by AAMI to report the results and evaluate the methods, making it difficult to make a fair comparison of the works published in the literature.

2.3. Summary

This chapter has reviewed the previous methods and techniques for heartbeat detection and arrhythmia heartbeat classification. This has provided the lead for the research methodology in this study. Based on the review, the technique and method for heartbeat detection, and approach for arrhythmia heartbeat classification have been identified and presented in the next chapter.

Chapter 3
Materials and Methods

In this chapter, the materials, methods and evaluation metrics used in this study are presented. Three types of ambulatory ECG signal data with different characteristics are identified and selected as materials for heartbeat detection and arrhythmia classification. To achieve the objectives, three approaches have been designed and methods for each approach are briefly described in this chapter. Lastly, the evaluation metrics used for both heartbeat detection and classification are presented.

3.1. Ambulatory ECG Signal Data

Three types of ambulatory ECG signal are used in this study: MIT-BIH Arrhythmia (MIT-BIH) database, ECG-Noise Simulated signal and Glasgow University database (GUDB) as presented in Table 3.1. The MIT-BIH database [75] is a standard database that has been used as a standard reference for most of the published research in heartbeat and arrhythmia detection areas. It was selected as the clean ECG signal in this study since it was recorded in a supervised clinical environment using a Holter monitor, showing high quality of the ambulatory signal. The ECG-Noise Simulated signal was represented as the ECG signal contaminated with different intensity level of noises from low to high noise of the ambulatory environment. The signal was generated using clean signal and noise sources specifically recorded from physically active movements. The GUDB database is an online public database of ECG recordings with annotated R peaks recorded during realistic movement conditions. They were realistic data to assess the performance of heartbeat detection algorithms [76].

Table 3.1. Summary of Datasets

Characteristics	Data		
	MIT-BIH	Simulated Signal	GUDB
Device Type	Holter Monitor	Holter Monitor	Wireless Devices (Attys Wireless Bluetooth Devices)
Frequency Sampling	360 Hz	360 Hz	250 Hz
Duration	30 minutes	30 minutes	2 minutes (for each activity)
Signal Type	MLII	MLII	V1-V2 (Chest strap) Lead II– Lead III (Standard Cable)
Records	48 records	48 simulated signals (with BW, MA and EM noise sources with -12 dB to 12 dB intensity level)	25 records (25 candidates)
Activity	N/A	N/A	5 Activity
Age	23 to 89	23 to 89	Over the age 18
Health Information	Yes	Yes	No

3.1.1. MIT-BIH Arrhythmia Database

The MIT-BIH is a public database freely available on Physionet website at www.physionet.org [77]. The database was the first set of standard test material generally available to evaluate arrhythmia detection, and it has been used to evaluate heartbeat detection and ECG analyses. This database has also been used for the basic research for cardiac arrhythmias at about 500 sites worldwide [77]. The Physionet website offers not only the web access to large collections of recorded physiological signals (PhysioBank), but also the related open source software (PhysioToolkit) and several other important utilities and information related to ECG signal analysis. The varieties of ECG data signals available on this website have been extremely useful to the researchers to implement various algorithms in offline ECG analysis. For all databases in Physionet, the AAMI

[78] recommendations for class labeling were adopted, including MIT-BIH as explained below.

3.1.1.1. Data Description

The MIT-BIH database consisted of two-channel ECG signals that include both normal and arrhythmic beats. In most records, the upper signal is a modified limb lead II (MLII), obtained by placing the electrodes on the chest. The lower signal is usually a modified lead V1 (occasionally V2 or V5, and in one instance V4); as for the upper signal, the electrodes are also placed on the chest. Normal QRS complexes are usually prominent in the upper signal [77]. The database contained 48 recordings, each was 30-minutes long with a sampling rate of 360 Hz from 47 male and female subjects aged between 23 to 89 years old studied by the BIH Arrhythmia Laboratory. Note that record 201 and 202 came from the same subject.

These 48 records were selected from a set of 4000 24-hour ambulatory ECG recordings during daily life activities of each subject, collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital. It included 23 randomly chosen records (the "100 series" recording number) and 25 selected records (the "200 series" recording number) to include examples of uncommon but clinically important arrhythmias that would not be well represented in a small random sample. The first group was intended to serve as a representative sample of the variety of waveforms and artifact that an arrhythmia detector might encounter in a routine clinical use. The records in the second group included the complex ventricular, junctional, and supraventricular arrhythmias and conduction abnormalities. Several of these records were selected because of the features of the rhythm, QRS morphology variation, signal quality that might present significant difficulties to arrhythmia detectors which gained considerable notoriety among database users [77]. The database included the annotation files that contained marked locations of each QRS complex, and types of arrhythmias by two or more cardiologists. The details of the 48 records are presented in Table 3.2.

Table 3.2. The MIT-BIH Arrhythmia Database

Record	Beats						Record	Beats					
	Total	N[1]	S[2]	V[3]	F[4]	Q[5]		Total	N[1]	S[2]	V[3]	F[4]	Q[5]
100	2273	2239	33	1	0	0	201	1963	1635	128	198	2	0
101	1865	1860	3	0	0	2	202	2136	2061	55	19	1	0
102	2187	99	0	4	56	2028	203	2980	2529	2	444	1	4
103	2084	2082	2	0	0	0	205	2656	2571	3	71	11	0
104	2229	163	0	2	666	1398	207	1860	1543	107	210	0	0
105	2572	2526	0	41	0	5	208	2955	1586	2	992	373	2
106	2027	1507	0	520	0	0	209	3005	2621	383	1	0	0
107	2137	0	0	59	0	2078	210	2650	2423	22	195	10	0
108	1774	1740	4	17	2	0	212	2748	923	1825	0	0	0
109	2532	2492	0	38	2	0	213	3251	2641	28	220	362	0
111	2124	2123	0	1	0	0	214	2262	2003	0	256	1	2
112	2539	2537	2	0	0	0	215	3363	3195	3	164	1	0
113	1795	1789	6	0	0	0	217	2208	244	0	162	260	1542
114	1879	1820	12	43	4	0	219	2154	2082	7	64	1	0
115	1953	1953	0	0	0	0	220	2048	1954	94	0	0	0
116	2412	2302	1	109	0	0	221	2427	2031	0	396	0	0
117	1535	1534	1	0	0	0	222	2483	2274	209	0	0	0
118	2278	2166	96	16	0	0	223	2605	2045	73	473	14	0
119	1987	1543	0	444	0	0	228	2053	1688	3	362	0	0
121	1863	1861	1	1	0	0	230	2256	2255	1	0	0	0
122	2476	2476	0	0	0	0	231	1571	1568	1	2	0	0
123	1518	1515	0	3	0	0	232	1780	398	1382	0	0	0
124	1619	1536	31	47	5	0	233	3079	2230	7	831	11	0
200	2601	1743	30	826	2	0	234	2753	2700	50	3	0	0

[1] Normal (N), [2] Supraventricular Ectopic (S), [3] Ventricular Ectopic (V), [4] Fusion (F), [5] Unknown (Q)

3.1.1.2. AAMI Class Labeling Recommendation

The ANSI/AAMI EC57:1998/(R) 2008 standard was developed by AAMI [78], defining the protocol to perform the evaluation for ECG analysis. It also specifies how annotations should be done in the databases. An example can be seen in Figure 3.1, in which the lead II is at the upperpart of the figure, lead V1 at the lower, and some annotations in the center. According to the AAMI standard, the beat labels in the annotation files are individually labelled as one of 15 possible arrhythmias. These arrhythmias are grouped into five classes defined as follows: (1) N is a normal beat and any beat not in the S, V, F, or Q classes; (2) S is a supraventricular ectopic beat or known as SVEB; (3) V is a ventricular ectopic beat or called VEB; (4) F is a fusion of a ventricular and a normal beat; (5) Q includes the paced beat, a fusion of a paced and a normal beat, or a beat that cannot be classified. The details of the heartbeat types in each AAMI classes and formats used in the databases are presented in Table 3.3.

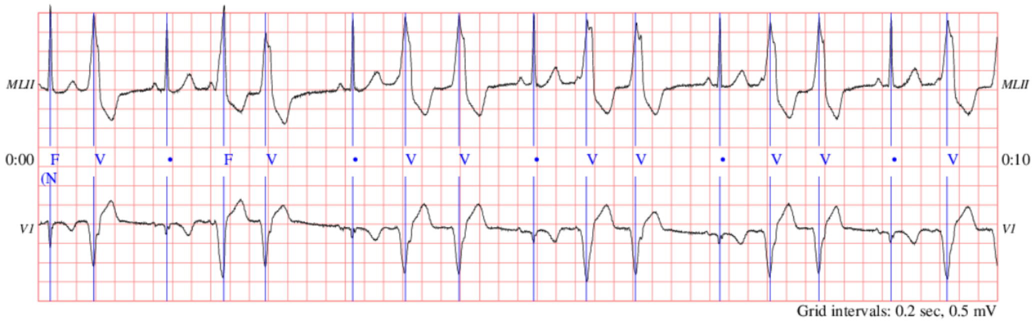


Figure 3.1. Example of annotations in a MIT-BIH database [77].

Table 3.3. AAMI Recommendations Annotation.

AAMI Classes	Description	MIT-BIH Annotation	MIT-BIH Heartbeat Type
N	Normal or any heartbeat not in the S, V, F or Q classes	N	Normal beat
		L	Left bundle branch block beat
		R	Right bundle branch block beat
		e	Atrial escape beat
		j	Nodal (junction) escape beat
S	Supraventricular ectopic beats	A	Atrial premature contraction
		a	Aberrated atrial premature beat
		J	Nodal (junctional) premature beat
		S	Premature or ectopic supraventricular beat
V	Ventricular ectopic	V	Premature ventricular contraction

	beats	E	Ventricular flutter/fibrillation
F	Fusion beats	F	Fusion of ventricular and normal beat
Q	Unknown beats	P	Paced beat
		f	Fusion of paced and normal beat
		Q	Unclassifiable beat

3.1.2. ECG-Noise Simulated Signal Data

The ECG-Noise simulated signal was created using recordings from MIT-BIH as clean signal and noise sources from the MIT-BIH Noise Stress Test Database (MIT-NST) [79]. The MIT-NST Database includes three half-hour records of noise typical in ambulatory ECG recordings. The noise recordings were made using physically active volunteers and standard ECG recorders, leads, and electrodes of which the electrodes were placed on the limbs of the subjects. The noise records were assembled from the recordings by selecting the intervals that contained predominantly BW, MA and EM, and then were collected as a noise source individually. The three noise sources of BW, MA and EM from MIT-NST database were used in this study.

The signal was produced using a scheme shown in Figure 3.2 in which the simulated signal was produced by separately adding three sources of noise to a clean ECG signal. The noises were directly added to the aforementioned original ECGs with different intensity level of noises from low to high noise, measured using SNR. To simulate different levels of noise, the SNR from -12 to 12dB in steps of 3dB was used. The SNR was calculated using the following Equation (3.1):

$$SNR = 10\log_{10}\frac{Psignal}{a \times Pnoise} \tag{3.1}$$

where P denotes the signal power and a refers to a scale factor.

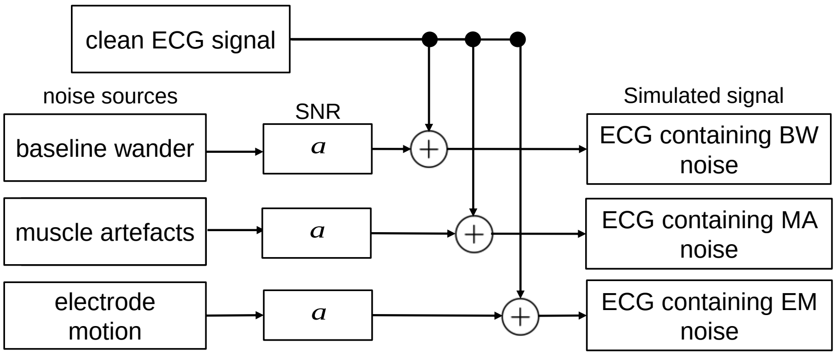


Figure 3.2. Scheme to generate the ECG-Noise simulated signal.

All 48 records from the MIT-BIH Database as presented in Table 3.1 [77] were used to generate the ECG-Noise simulated signals. The records numbered 100, 200 and 213 were selected for further analysis to determine the effects of beat detectors performance on noise signals and abnormal beats in ECG, and then were evaluated based on the proposed heartbeat detection and heartbeat classification system. The record 100 was selected as the clean signal as it was of good quality compared to the other signals and it contained a few arrhythmia beats while the record 200 and 213 were selected as an arrhythmia signal due to their dynamic signal that consisted of a fusion of arrhythmias beats. Since the original ECG recordings were clean, the correct beat annotations and arrhythmia detection were known even when the noise makes the recordings visually unreadable. The reference annotations for these records were simply copies of those for the original clean ECGs. Examples of simulated ECG signals with different levels of SNR are shown in Figure 3.3.

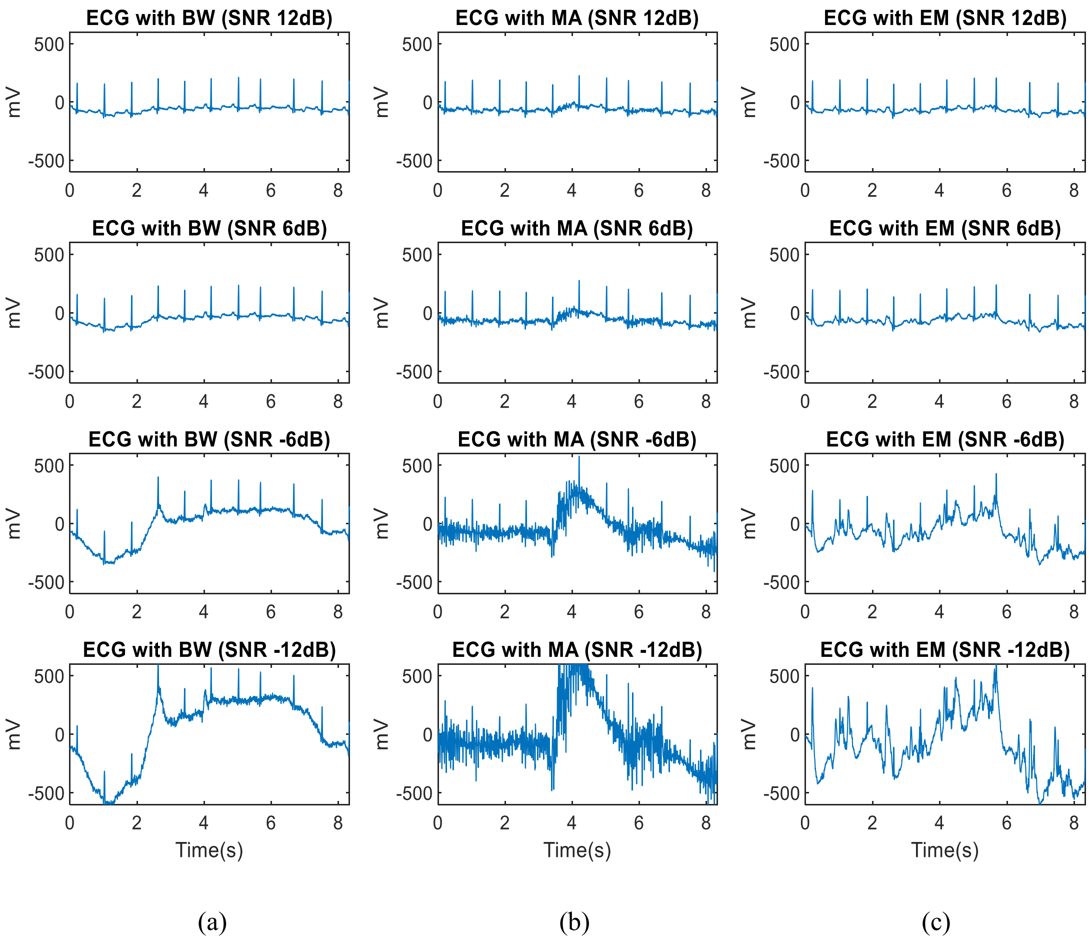


Figure 3.3. Example of simulated ECG signals that contain noise with SNR 12, 6, -6, -12 dB: (a) ECG signal with BW; (b) ECG signal with MA; (c) ECG signal with EM artifact.

3.1.3. Glasgow University Database

The Glasgow University Database (GUDB) is an online public database of ECG recordings with annotated R peaks recorded and filmed under realistic movement conditions by College of Science and Engineering, University of Glasgow [76]. This database provides the ECG recording during the movement condition, such as walking and running, serving as a realistic data to assess the performance of heartbeat detection algorithms [76]. The database is available online upon request on the University of Glasgow website at http://researchdata.gla.ac.uk/716/.

In the database, the ECG signals were recorded using an Attys Bluetooth data acquisition board by Glasgow Neuro LTD, Glasgow. This board had a sampling rate of

250 Hz and a resolution of 24-bit over a range of ±2.42 V. As this device was wireless, it increased electrical isolation and allowed a moving subject to be recorded easily without the need of a cumbersome tether. Two Attys devices were used at the same time to record three following channels that ran synchronously: (1) Exercise chest strap ECG which approximately resembled V2 and V1 with the ECG amplifier directly mounted on the strap; (2) Einthoven II and III with standard cables and the amplifier worn around the waist; and (3) Acceleration in X/Y/Z with the sensor mounted directly on the chest strap. The circuit diagram for the configuration is depicted in Figure 3.4 A and an example of chest strap and wiring of the amplifier is shown in 3.4 B. Figure 3.4 C and 3.4 D are examples of the signal in this database while the subject is jogging. The chest strap recording remained largely noise free while the Einthoven signal had a significant noise contamination.

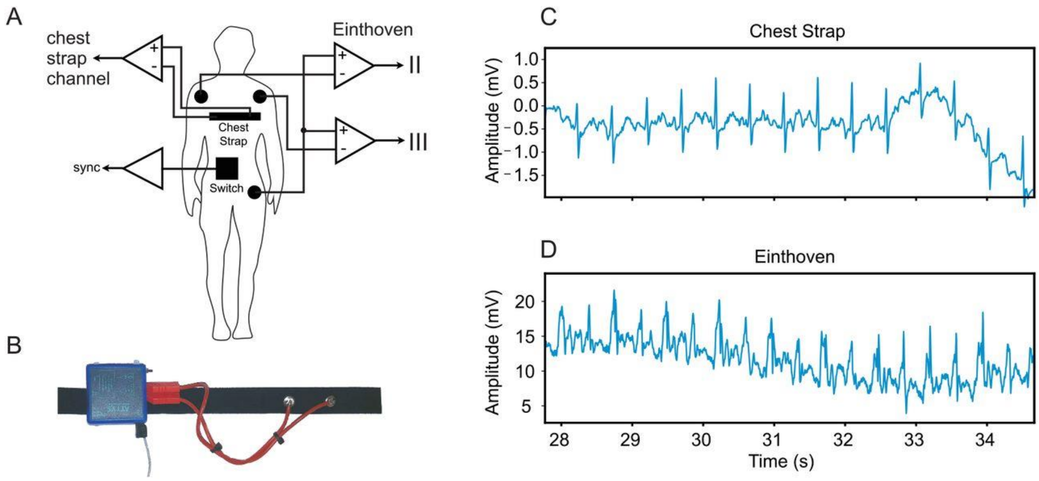


Figure 3.4. The configuration and example ECG signal of GUDB [76].

The database consists of two-minutes ECG recordings from 25 male and female subjects over the age of 18 without any known cardiovascular conditions. Each subject was recorded performing five different tasks which were sitting, using a tablet to perform a mathematic test, walking on a treadmill, using a hand-bike and jogging for two minutes each in a laboratory environment. Figure 3.5 shows the example of ECG signal and tri-axis acceleration signal recording during the movement activity. The procedure of the recording is as follows [76]:

1. The subject will put on the chest strap and electrodes. The paper electrodes will be

attached as follows: one on the right shoulder, one on the left shoulder and two on the left hip. Then, the Attys devices will be connected.

2. 120 second ECG recording when the subject is sitting down;
3. 120 second ECG recording during performing a mathematic test;
4. 120 second break;
5. 120 second ECG recording during walking on a treadmill at 4 KPH;
6. 120 second break;
7. 120 second ECG recording while using the hand bike;
8. 120 second break;
9. 120 second ECG recording during jogging on a treadmill at 8 KPH;
10. Electrodes and chest strap will be removed from the subject.

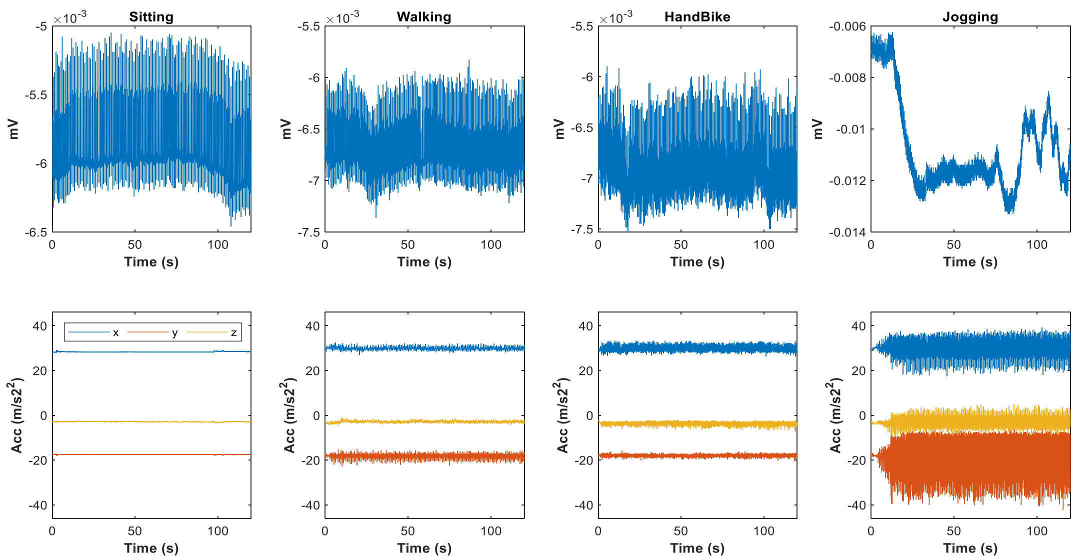


Figure 3.5. Example of ECG signal and tri-axis acceleration signal of GUDB databases.

In order to be able to link the ECG artifacts to the behavior of the subject, the subject gave permission to be filmed and the videos were also part of the database. For the annotation of the heartbeats, the sample locations of heartbeats have been annotated for both of the chest strap and Einthoven cables recordings. The annotations were generated first by an automatic detection algorithm and then visually checked and corrected so that every heartbeat was correct. However, not all ECG recordings were provided with the annotation files because there was too much noise in the recording to be reliable for the annotation. Therefore, only nine ECG recordings from nine subjects that had annotations files were used in this study. The Einthoven signal from nine recordings was chosen because they represented the ECG morphological sample similar to MT-BIH.

3.2. Methods

Three approaches were designed to achieve the objectives, and several methods and experiments have been implemented. The first approach included the methods to investigate the effects of ECG noise on heartbeat detection algorithm performance; the second approach contained the method to develop the detection of heartbeat in the noisy signal; while the third approach contained the methods to classify the heartbeat to detect the arrhythmias. All the experiments presented in this study were programmed in MATLAB R2018b and performed in 64-bits Windows 10 PC with i7-7Y75 CPU and 16GB memory. The overview of the method employed is presented in this section.

Objective 1: To study and analyze the effects of noisy signal on the heartbeat detection performance for ambulatory arrhythmia monitoring.

The relationship between the ECG noise and heartbeat detection performance has the potential to evaluate the effects of noisy ECG signals. Therefore, a methodology to compare a set of QRS detector performance using the ECG signal with different noise conditions was developed to study their effects. For this purpose, three well-known QRS detection algorithms were employed: the Pan Tompkins [9], the WQRS [11] and the Hamilton [10] algorithms. The main criteria for the algorithm selection were that the algorithm could be applied in a real-time system and it showed robust performance against the noisy and ambulatory ECG signals. Experiments were performed to determine the effects of beat detector performance on clean ECG signal, heartbeat morphology, noisy signal and abnormal signal. The standard database and simulated data using the BW, MA and EM with different levels of SNR were utilized, and the three algorithms were used to perform the heartbeat detection process. The effects of noise artifacts in the ECG signals that degraded the heartbeat detection performance were analyzed. The details of the experiments and results for this approach will be specifically described in Chapter 4.

Objective 2: To propose a noise-tolerant QRS detection method and improve the detection performance for a noisy signal.

The noise-tolerant QRS detection method was proposed and developed in this study. The proposed method consisted of two phases: the pre-processing and QRS detection phase. Five steps have been employed in the pre-processing phase, starting with the band-pass filter, derivative, squared, SGMA smoothing and autocorrelation. The band-pass filter with 8-20 Hz was used to increase the signal quality while the SGMA and autocorrelation technique was adopted to smooth the signal data and prevent incorrect detection. The proposed pre-processing phase was combined with the adaptive threshold in the QRS detection phase to identify the right peak. Three experiments were done using different conditions of ambulatory ECG signal to evaluate the capability of the proposed method on the noisy ECG signal. The performance of the proposed method was evaluated and compared with other QRS detection method and presented in this study. The details of the experiments and results of the proposed QRS detection method are described in Chapter 5.

Objective 3: To develop the arrhythmia detection system for ambulatory ECG signal using heartbeat classification approach.

The heartbeat classification approach was designed and implemented for the detection of arrhythmias. Four main steps were employed in this approach: 1) pre-processing, 2) QRS detection, 3) feature extraction, and 4) classification. In the pre-processing and QRS detection phases, the propose noise-tolerant QRS detection method was implemented as described in Chapter 5. Two groups of the feature that can represent heartbeat were constructed in the feature extraction phases. Five heartbeat interval features and eight ECG morphology features were extracted. Lastly, the classification model was developed using classification algorithms. Four different classification algorithms which were k-nearest neighbor algorithm, support vector machine, decision tree, and linear discriminant were used to obtain the best classification model. Then, the best learning model was validated using the ambulatory ECG signal data, and the results were presented. The details of methods and experiments for this approach will be specifically described in Chapter 6.

3.3. Evaluation Metrics

Four evaluation metrics were used in this study: sensitivity (SE), positive predictivity (PP), error detection rate (DER) and accuracy (ACC). SE, PP and ACC have been recommended by AAMI [78] for evaluating heartbeat detection and arrhythmia classification while DER was used to evaluate noise improvement for ECG analyses. Generally, SE denotes the percentage of true positive beats that are correctly identified, PP denotes the percentage of detected true beats, DER denotes the percentage of the error detection beats and ACC is a total percentage of correctly identified beats. The SE, PP, DER and ACC were calculated using Equations (3.2), (3.3), (3.4) and (3.5), respectively [40, 80]:

$$SE = \frac{TP}{TP + FN} \times 100\% \tag{3.2}$$

$$PP = \frac{TP}{TP + FP} \times 100\% \tag{3.3}$$

$$DER = \frac{FP + FN}{TP + FP + FN} \times 100\% \tag{3.4}$$

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \tag{3.5}$$

where TP denotes the true positive, TN is the true negative, FP is the false positive and FN is the false negative. The total of TP, TN, FP and FN was calculated using confusion matrix as shown in Figure 3.6. The confusion matrix [6] is a tool for predictive analysis and it can be used to describe the performance of a statistical classification model on a set of test data for which the true values are known or called actual condition. In the confusion matrix, each predicted condition case is identified to four categories: TP is a correctly predicted positive case, TN is a correctly predicted negative case, FP is an incorrectly predicted positive case and FN is an incorrectly predicted negative case.

<table>
<tr><td colspan="2"></td><td colspan="2">Predicted Condition</td></tr>
<tr><td></td><td>Total</td><td>No</td><td>Yes</td></tr>
<tr><td rowspan="2">Actual Condition</td><td>No</td><td>True Negative (TN)</td><td>False Positive (FP)</td></tr>
<tr><td>Yes</td><td>False Negative (FN)</td><td>True Positive (TP)</td></tr>
</table>

Figure 3.6. The confusion matrix terminology.

3.4. Summary

This chapter detailed the materials and methodology used in this study. The description included the selection of the ambulatory ECG signal data and the evaluation metrics. The data prepared in this chapter were suitable to be used for the experiments since all the data were recorded in the ambulatory environment and supplemented with annotation files. While designing and constructing the heartbeat detection and arrhythmia detection method, the overview of the approaches was described. Since this study used the statistical classification algorithms for constructing the model, the confusion matrix was employed. The confusion matrix was introduced and four evaluation metrics were presented in this chapter.

Chapter 4
Effects of Noisy Signal on Heartbeat Detection Performance

4.1. Introduction

The analysis of the effects of ECG noise on heartbeat detection performance has been conducted by previous researchers [13, 42-43]. However, the previous study [43] used different categories to evaluate the performance of heartbeat detection. The noise types and level of intensity of noises from the ambulatory environment that affects the QRS detection performance are not clearly described in this study. Another study [13] has highlighted a few noises and artifacts from the ambulatory environment. Nevertheless, the study [13] did not use the real ECG noise from ambulatory recordings to evaluate the detection performance. In addition to that, they also used a conventional scheme to quantify the noise in the ECG signal. Matteo et al. [42] have evaluated the heartbeat detection performance using the ECG signal and noise from ambulatory recording. The SNR measurement has also been used to present the detection results. However, the performance of the heartbeat detection only evaluated the electrode motion artifact. The comparison between other noises was not investigated. Moreover, they did not consider high noise in their studies.

Therefore, in this chapter, we investigated the effects of noise from ambulatory recording on heartbeat detection performance. The methodology to compare a set of QRS detectors under different noise conditions was presented. Three main experiments were performed to determine the effects of beat detector performance on clean ECG signal, heartbeat morphology and noisy signal. The standard database and noise source from real ECG recordings were used in this study. This differed from a previous study [13] in which they did not use the real ECG noise from ambulatory recordings. Different from another study [42], in this chapter, the experiment was conducted on different levels of SNR including the highly noisy signal of -12dB. Three noise sources, BW, MA and EM, were utilized and three threshold-based algorithms were used to perform the beat detection process.

4.2. Heartbeat Detection Algorithms

Three algorithms were employed in this study to represent the threshold-based heartbeat detectors: the Pan Tompkins [9], the WQRS [11] and the Hamilton [10] algorithms. The main criteria for the algorithm selection were that the algorithm could be applied in a real-time system and they showed a robust performance with the noisy ECG signals. The Pan Tompkins and Hamilton algorithm were implemented using the MATLAB software. Meanwhile, the WQRS algorithm downloaded from the PhysioNet website [81] was called using MATLAB scripts as the MATLAB external function. The correctness of the algorithm implementation was verified by analyzing the results with the same data, in this case, a record from the MIT-BIH Database. It was observed that the results obtained were almost similar to the ones reported in previous studies [9-11].

The Pan Tompkins algorithm [9] is one of the most well-known heartbeat detection algorithms. This algorithm used band-pass filtering, signal differentiation, squaring, moving window integration and two sets of adaptive thresholds to filter and integrate signals for heartbeat detection. The first step was a band-pass filtering with a passband of 5−15 Hz, which removed the BW, and a 50 Hz power line interference that reduced the amplitude of T-waves. After the band-pass filtering step, the signal was differentiated to highlight the sharp slopes of the QRS complex. To further emphasize the QRS complex, the signal was squared to obtain positive values. The final processing step involved a moving window integration with an average window of 150 ms. This window was chosen to match the width of the widest possible QRS complex. The QRS peaks of at least 300ms apart were identified in the pre-processed signals and classified as a noise or a QRS complex depending on the adaptive threshold.

The WQRS [11] algorithm is based on the slope and length transform of the ECG signal to identify the QRS complex. The algorithm used low pass filters, non-linearly scaled curve length transformation and decision rules to determine the location of corresponding QRS. Instead of the band-pass filter, the low pass filter was used to eliminate the BW artifacts. The low pass filter of 16 Hz was employed to suppress the high-frequency components. Then, the ECG signal was transformed into a curve length signal using a non-linear scaling factor to enhance the QRS complex and suppress the unwanted noise. The QRS complex was determined using an adaptive threshold in the decision rules process.

The Hamilton [10] algorithm is based on the work by Pan and Tompkins [9] with alterations carried out for the pre-processing stage. The Hamilton algorithm used band-pass filtering, differentiation, rectifying, moving window average and three rules threshold to identify the QRS complex. It differed from Pan Tompkins and WQRS algorithms because the band-pass filter of 8–16Hz was used to remove the high and low-frequency noises. After the band-pass filtering step, the differentiated signal was rectified instead of squaring to highlight the QRS complex. To match the possible QRS complex in the signal, the 80ms moving average window was used. The QRS peak of at least 300ms away from the last detected R-peak and the peak amplitude above the detection of the adaptive threshold was classified as a QRS complex.

4.3. Analysis of ECG Signal on Heartbeat Detection Performance

In this section, the analysis performance of heartbeat detector on clean ECG signal, effects of noisy signal on heartbeat morphology and performance of detector on noisy signal and abnormal signal are presented. The relationship between the ECG noise and heartbeat detection for ambulatory cardiac monitoring using heartbeat detection algorithms for both clean and noise-simulated ECG was investigated. The effects of noise and artifacts in the ECG signals that degraded the heartbeat detection performance were also discussed. To validate the heartbeat detection performance, each detected QRS peak was categorized as TP, FP or FN. Specifically, TP denotes the total number of QRS peaks detected as the QRS complex, FP denotes the total number of non-QRS peaks or noises detected as the QRS complex and FN represents the total number of QRS complexes that was not detected. Two evaluation metrics which were SE and PP were calculated using Equations (3.2) and (3.3) as described in Chapter 3. The SE denotes the percentage of true beats correctly detected by the algorithm whereas the PP denotes the percentage of detected true beats.

4.3.1. Effects of Beat Detector Performance on a Clean ECG Signal

The heartbeat detector performance on a clean ambulatory ECG signal was evaluated using 48 records from the MIT-BIH Database (Table 3.2. in Chapter 3) [77]. The clean ECG signal was used to investigate the reliability of the algorithms' performance with high quality ambulatory ECG signal that contained a diverse arrhythmia beat. Figure 4.1 presents the average performance of the three algorithms of beat detectors on all 48 ECG records. There was no significant difference found in the performances of these algorithms when using a clean ECG. All the algorithms produced SE and PP with an average above 98%, indicating a good performance of the algorithms for both clean and diverse clinical ECG signals from 47 subjects.

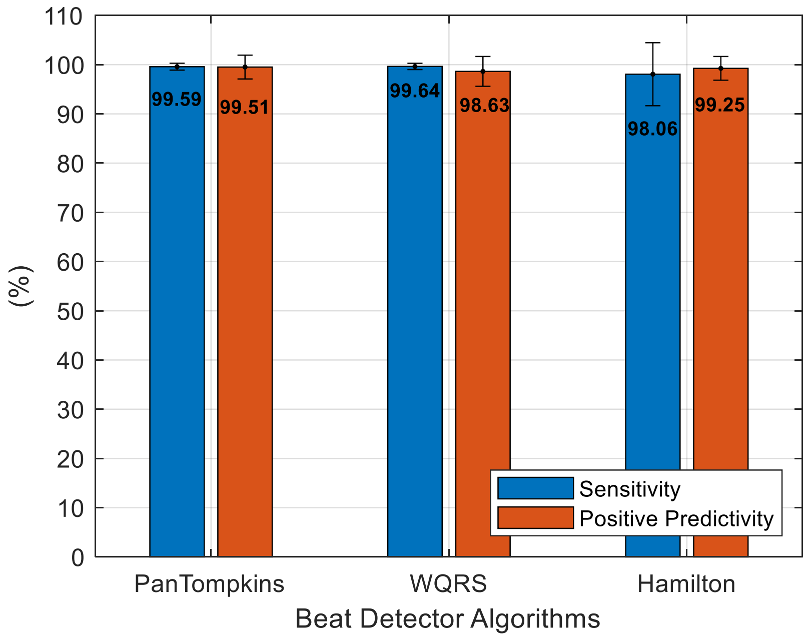


Figure 4.1. Beat detector algorithm performance on a clean data.

The Hamilton algorithm had a good PP; however, the SE decreased which indicated that the algorithm was sensitive towards the abnormalities of heart rhythm. Although the WQRS algorithm was capable of detecting the correct QRS peak with the highest total SE of 99.64%, the algorithm was also sensitive to noise. The WQRS algorithm often detected false peak as the QRS complex, thus producing a low PP. The Pan Tompkins algorithm also had the stability to perform heartbeat detection compared to the other two methods with 99.59% of SE and 99.51% of PP, respectively.

All beat detector algorithms performed well for most of the records in the MIT-BIH Database [77]. Nevertheless, in this database, there was a few records, such as record numbers 105, 108, 121, 200, 202, 207, and 217, that had dynamic signals due to the abnormal beats and noise effects. Previous research also used these records to assess the noise robustness [82-83]. According to the PhysioNet web-based resource [77], the signal from record 207 is the extremely difficult record in the MIT-BIH Database due to the predominant rhythm of abnormal beats in the signal. In this study, a comparison of the algorithm performance for the few difficult records such as record numbers 105, 108, 121, 200, 202, 207, and 217 was also carried out as shown in Table 4.1.

Table 4.1. Comparison of the beat detector performances for ECG record 105, 108, 121, 200, 202, 207 and 217.

Record	Pan Tompkins [9]		WQRS [11]		Hamilton [10]	
	SE (%)	*PP* (%)	*SE* (%)	*PP* (%)	*SE* (%)	*PP* (%)
105	99.46	98.27	98.83	92.10	99.57	98.88
108	99.77	83.27 [1]	99.38	84.19 [1]	99.32	99.38
121	99.89	100	99.79	99.73	99.95	100
200	99.85	99.85	99.85	99.31	99.85	99.73
202	99.53	100	99.81	99.95	99.67	100
207	98.98	99.68	99.41	98.40	99.25	99.84
217	99.82	99.91	99.55	98.30	99.18	99.64

[1] Low positive predictivity.

The findings showed that the beat detector could handle both normal and abnormal beat signals such as record numbers 200, 202, 207, and 217. The signal from the record 200 indicated a normal and combination of ventricular beats while the signal from the record 202 showed a normal, atrial premature and premature ventricular contraction beat. The ECG signal of the record 217 was composed of normal beats with a fusion of paced and premature ventricular contraction beats. The results showed that the beat detectors performance with this signal resulted in the percentage of SE and PP above 98.98% and 98.2%, respectively. Furthermore, while the signal from the record 121 was distorted by the BW, it did not affect the detection performance. However, the performance of the beat detector degraded especially with the signal from the record 108 that was influenced by MA and low amplitude, and the signal from the record 105 that was contaminated with high-grade noise.

4.3.2. Effects of Noisy Signal on Heartbeat Morphology

In this section, the effects of noise in ECG signal towards the heartbeat morphology were studied. Simulated signals using the record number 100 from MIT-BIH Database that were contaminated with BW, MA, and EM with SNR of 0 dB were evaluated separately to investigate the heartbeat morphologies affected by noisy signals. The Pan Tompkins [9] algorithm was chosen due to the comprehensive approach to reduce the interferences and to avoid false detections of QRS complexes in ECG signals. The algorithm also had higher accuracy for various beat morphologies than the other traditional real-time methods [84]. The QRS characteristics of heartbeat morphologies were evaluated after the band-pass filtering process with 5 to 15 Hz and adaptive thresholds of Pan Tompkins algorithm to reduce the destruction caused by the noises and identify the true beats in ECG signals. Figure 4.2 shows the ECG morphologies as affected by noisy and de-noised signals.

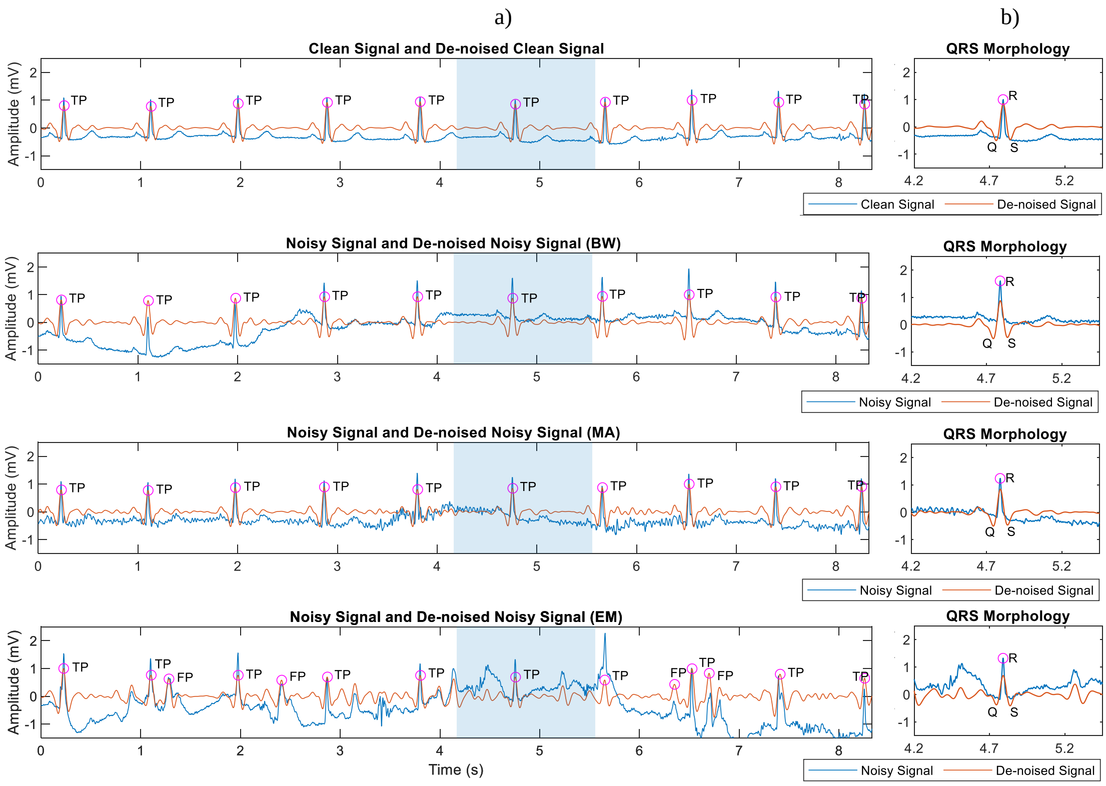


Figure 4.2. Visuals of the ECG morphologies as affected by clean and noisy signals with a SNR of 0 dB (a) ECG Signal and De-Noised ECG Signal; (b) the QRS morphologies of heartbeat.

As can be seen in Figure 4.2, the blue and orange signal represents the signal before and after the filtering process, respectively. The TP denotes true positive while FP denotes the false detection. The blue areas in Figure 4.2 (a) represent the QRS morphology in Figure 4.2 (b). The findings showed that the ECG morphologies were distorted by the different noises. The BW noise resulting from the subject's respiration movements presented an abrupt drift that introduced some interference to the signal. The MA noise with the high-frequency range interfered with the morphological features in the signal. Besides that, the ECG information changed when motion artifacts were introduced to the signal, causing irregularities in the ECG morphology. The difference in frequency ranges of BW, MA and EM artifact led to the distorted ECG signal morphologies.

In this study, the filtering process smoothened the ECG morphology and enhanced the QRS complex. Although the signal contaminated with BW and MA degraded the morphology, the algorithm managed to discover the QRS complex after the filtering process. However, the irregularities caused by the EM artifact could not be solved using the band-pass filter, thus resulting in a false detection as shown in Figure 4.2. It could be observed that the ECG signals contaminated with EM noise had the poorest signal compared to the other noises. The presence of undesired interferences from high-frequency noises caused a serious problem in the ECG diagnosis.

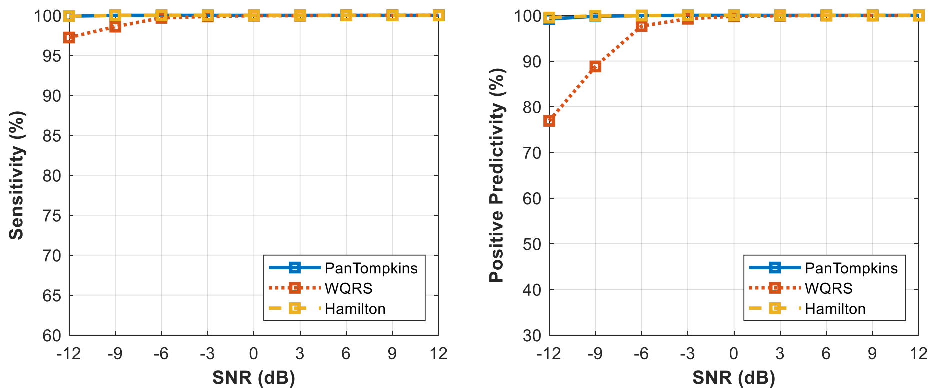
4.3.3. Effects of Beat Detector Performance on Noisy Signal

The effects of a heartbeat detector on the different intensity of noise was investigated. The simulated signals contaminated with BW, MA and EM were used to investigate the relationship between the heartbeat detection performance and the intensity of noise. Three experiments were done to evaluate the effects of noisy signal: (1) with the noise-simulated signal record 100 of MIT-BIH Database as it was of good quality compared to other signals and it contained a few arrhythmia beats; (2) with the noise-simulated signal record 200 of MIT-BIH Database that contained dynamic signal consisted of a fusion of arrhythmias beats; and (3) with the noise-simulated signal of all 48 records of noisy ECG signals and analyses of the average performance of heartbeat detection.

4.3.3.1. Noisy Signal on Record 100 of MIT-BIH Database

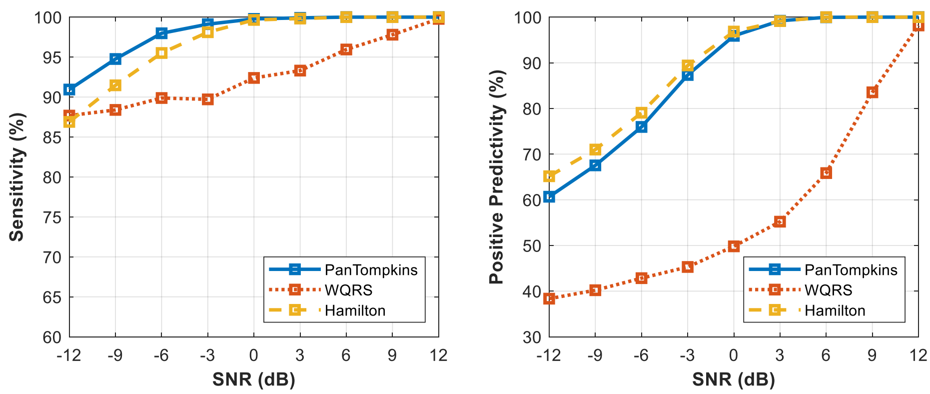
The effects of a heartbeat detector on different levels of noise in the clean ECG signal and signal that consisted of a few arrhythmia beats were determined. Figures 4.3 to 4.5 demonstrate the relationship between the performance of heartbeat detection and the level of noise. To evaluate the effects of noise contamination on arrhythmia signal, the record 100 from MIT-BIH Arrhythmia Database was used. The relationship between the different intensity of BW noise and the performance of heartbeat detection on the signal is shown in Figure 4.3. In response to the sensitivity of the three algorithms, at SNR levels above −6 dB, all the algorithms scored very well. At levels below SNR of −6 dB, the beat detector performance decreased, especially for the WQRS algorithm because the SE was lower, 97.23% at the SNR of −12 dB, indicating that the algorithm was sensitive to BW noise. In contrast, the Pan Tompkins and Hamilton algorithms possessed low SE at an SNR lower than −9 dB, where the SE of both the Pan Tompkins and Hamilton algorithms decreased to 99.92% and 99.91%, respectively. In terms of PP, the Hamilton and Pan Tompkins algorithms had a significantly better performance with 99.52% and 99.21%, respectively at −12 dB SNR of BW noise compared to the WQRS algorithm that had low performance with 76.9%.

Figure 4.3 shows the relationship between the different intensity of MA noise and the performance of heartbeat detection on the signal. Below the SNR of 3 dB, the performance of beat detector continued to decrease with the decreasing SNR value, with SE of 90.94% and 86.89% as produced by the Pan Tompkins and Hamilton algorithms, respectively at the SNR of −12 dB. The WQRS algorithm showed that the detector was very sensitive and unstable with MA, resulting in lower SE and PP performance. As for the PP, MA affected the performance of the Pan Tomkins and Hamilton algorithms at the SNR value below 3 dB. However, the Hamilton algorithm had a better PP (65.16%) at the SNR of −12 dB compared to the other two algorithms.



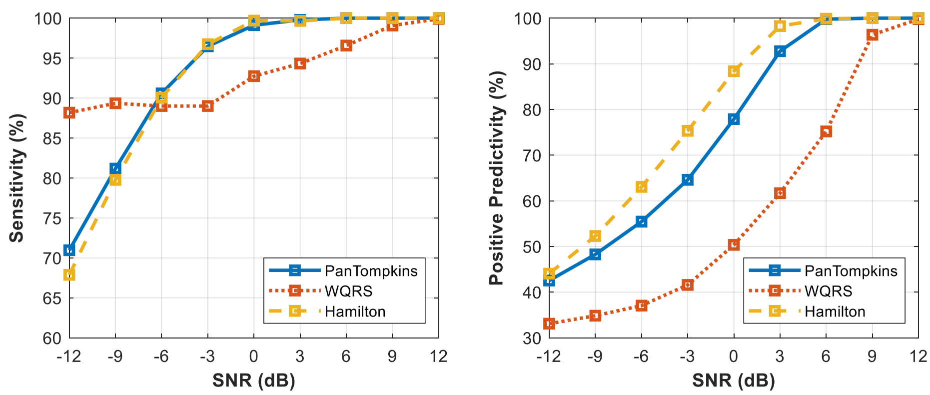
(a) (b)

Figure 4.3. Relationship between the performance of heartbeat detection and BW for the record 100: (a) SE and SNR; (b) PP and SNR.



(a) (b)

Figure 4.4. Relationship between the performance of heartbeat detection and MA for the record 100: (a) SE and SNR; (b) PP and SNR.



(a) (b)

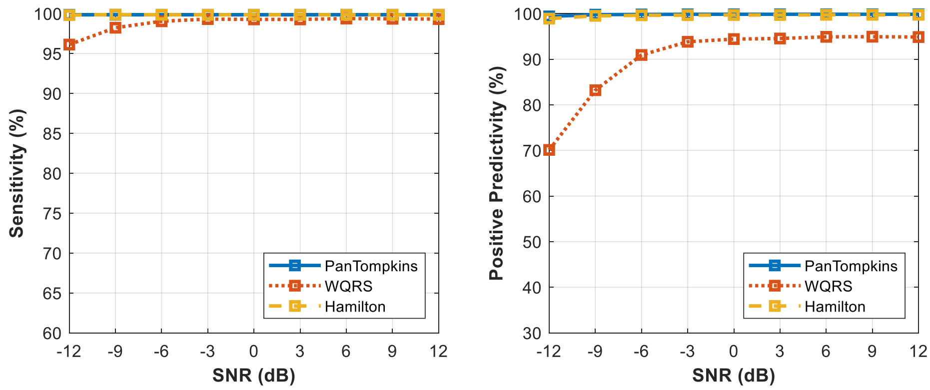
Figure 4.5. Relationship between the performance of heartbeat detection and EM artifact for the record 100: (a) SE and SNR; (b) PP and SNR.

The relationship between the intensity level of EM noise and the performance of heartbeat detection is shown in Figure 4.5. The signal contaminated with the EM artifact below the SNR of 0 dB degraded the detection performance of the Pan Tompkins and Hamilton algorithms. At the SNR of −12 dB, the Pan Tompkins and Hamilton algorithms decreased the SE to 70.96% and 67.88%, respectively, lower than the SE of WQRS algorithm which was 88.17%. This could be attributed to the high false-positive detection in the signal with high-frequency noises from EM artifact (Figure 4.5b), decreasing the PP of the detector performance. All three algorithms, the Hamilton, the Pan Tompkins and the WQRS, produced low PP with 44.05%, 42.54% and 33.09%, respectively at the SNR of −12 dB.

4.3.3.2. Noisy Signal on Record 200 of MIT-BIH Database

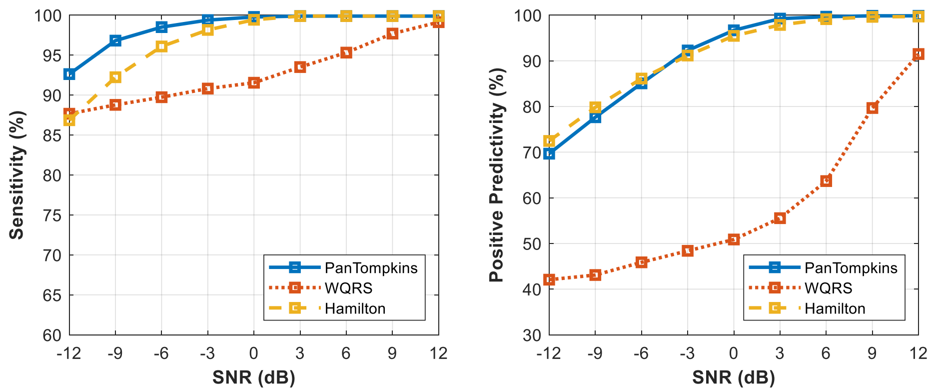
The effects of a heartbeat detector on different levels of noise in the ECG signal that consisted of both abnormal or arrhythmia beats were determined. Figures 4.6 to 4.8 demonstrate the relationship between the performance of heartbeat detection and the level of noise. To evaluate the effects of noise contamination on arrhythmia signal, the record 200 from MIT-BIH Arrhythmia Database was used. This record has a dynamic signal, consisting of a fusion of arrhythmias and normal beats [82].

The noise in the abnormal signal disrupted the heartbeat rhythm of arrhythmias morphology, thus degrading the ECG signal quality and affecting the heartbeat detection performance as shown in Figure 4.6. The BW noise affected the heartbeat detection process of the Pan Tompkins and Hamilton algorithms less compared to the WQRS algorithm. The SE as influenced by the Pan Tompkins, the Hamilton and the WQRS algorithms were 99.85%, 99.81% and 96.12%, respectively, with PP of 99.39%, 98.90% and 70.11%, respectively, at the SNR of −12 dB.



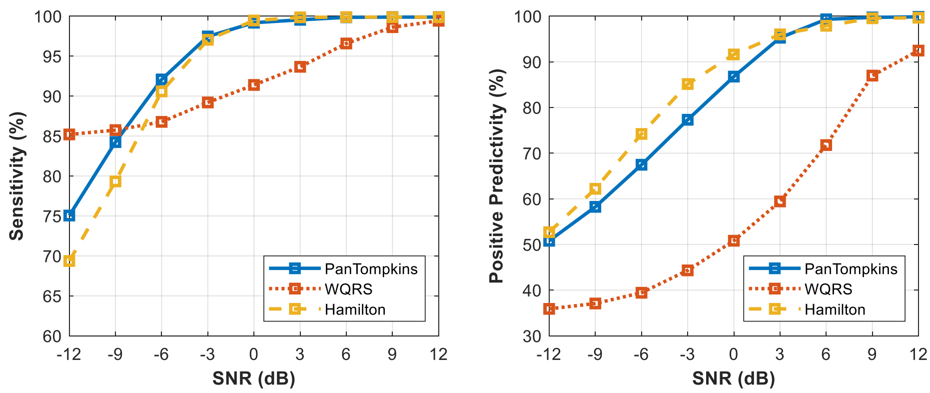
(a) (b)

Figure 4.6. Relationship between the performance of heartbeat detection and BW with abnormal signal for the record 200: (a) SE and SNR; (b) PP and SNR.



(a) (b)

Figure 4.7. Relationship between the performance of heartbeat detection and MA with abnormal signal for the record 200: (a) SE and SNR; (b) PP and SNR.



(a) (b)

Figure 4.8. Relationship between the performance of heartbeat detection and EM artifact with abnormal signal for the record 200: (a) SE and SNR; (b) PP and SNR.

Below the SNR of 3 dB, the detection of signal contaminated with MA noises in the abnormal signal reduced the SE (Figure 4.7. (a)). At the SNR of −12 dB, the Pan Tompkins, the WQRS and the Hamilton algorithms resulted in a SE of 92.62%, 87.66% and 86.85%, respectively, while at the SNR of −12 dB, the PP decreased to 69.66%, 42.07% and 72.45%, respectively (Figure 4.7. (b)). However, the signal contaminated with EM noises affected heartbeat detection. As shown in Figure 4.8, the EM artifact produced a lower performance of heartbeat detection with a lower SE of 69.36% at the SNR of 12 dB using the Hamilton algorithm. In contrast, the lower PP at the SNR of −12 dB for the signal contaminated with EM artifact was 35.9% using the WQRS algorithm, indicating the inability of this algorithm to manage the false positives in the detection process and performance maintenance.

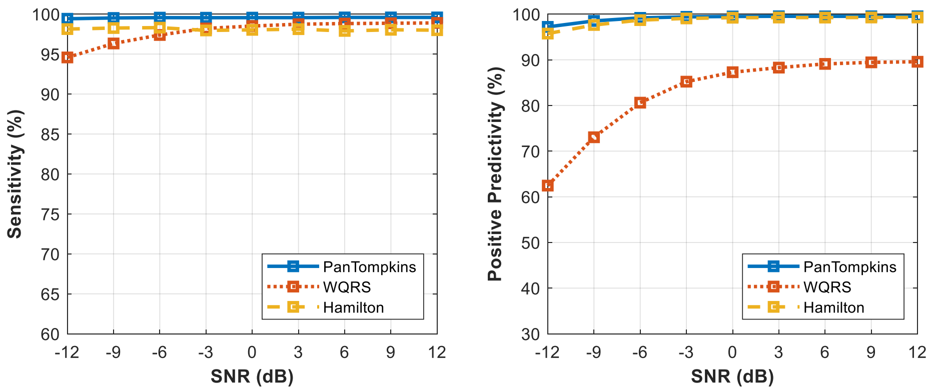
4.3.3.3. Noisy Signal on 48 Records of MIT-BIH Database

The effects of the different intensity of noise on the heartbeat detector method in 48 records from the MIT-BIH Arrhythmia Database were identified. The relationships between the heartbeat detection performance and the intensity of noise are exhibited in Figures 4.9–4.11. The SE and PP in Figures 4.9 to 4.11. (a) and (b) represented the average performance of heartbeat detection on all 48 records of noisy ECG signals.

Figure 4.9 shows the relationship between the different intensity of BW noise and the average performance of heartbeat detection. In response to the average sensitivity of the three algorithms, at the highest level of noise, all the algorithms were not able to detect all QRS complexes. The WQRS algorithm resulted in low SE (94.58%) at the SNR of −12 dB while the Pan Tompkins and Hamilton algorithms yielded a better performance with 99.42% and 98.13%, respectively. In terms of average PP, the Pan Tompkins and Hamilton algorithms had a significantly better performance with 97.21% and 95.74%, respectively, at −12 dB SNR of BW noise compared to the WQRS algorithm (62.45%).

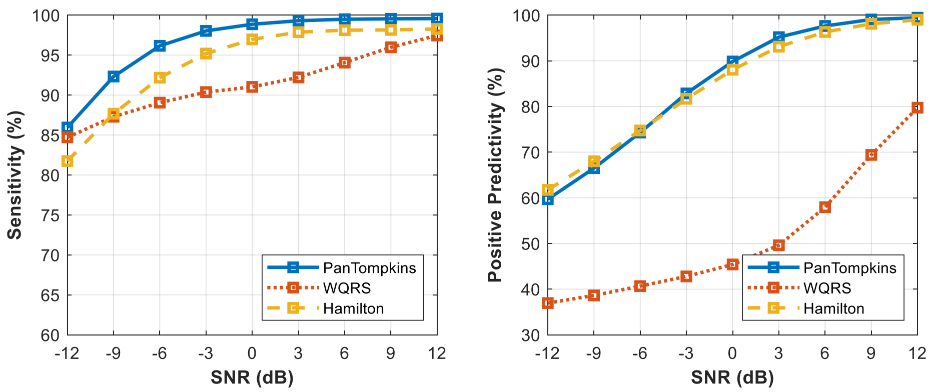
The relationship between the intensity level of MA noise and the average performance of heartbeat detection is shown in Figure 4.10. The MA noise affected the SE and PP of the heartbeat detection process of all algorithms. At the SNR of −12 dB, the average SE of the Pan Tompkins, Hamilton and WQRS algorithms were 85.94%, 81.74% and 84.71%, respectively and that of the PP was 59.68%, 61.74% and 36.95%, respectively. The WQRS algorithm showed that the detectors produced high false-negative detections, resulting in lower average PP performance at all levels of SNR compared to the Pan Tompkins and Hamilton algorithms (Figure 4.10. (b)).

Figure 4.11 shows that the signals contaminated with EM artifacts have degraded the detection performance of all algorithms. At the SNR of −12 dB, the Pan Tompkins and Hamilton algorithms decreased the SE to 68.85% and 65.44%, respectively, which were lower than the corresponding value of the WQRS algorithm (84.10%). As for the PP, the EM affected the average performance of algorithms at all SNR values. All algorithms, Hamilton, Pan Tompkins and WQRS, produced low PP with 44.05%, 42.54% and 33.09%, respectively, at the SNR of −12 dB.



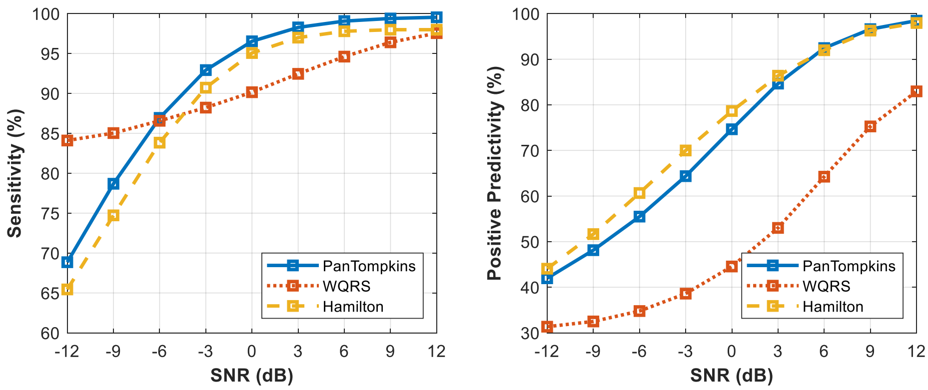
(a) (b)

Figure 4.9. Relationship between the performance of heartbeat detection and BW for all the 48 records: (a) SE and SNR; (b) PP and SNR.



(a) (b)

Figure 4.10. Relationship between the performance of heartbeat detection and MA for all the 48 records: (a) SE and SNR; (b) PP and SNR.



(a) (b)

Figure 4.11. Relationship between the performance of heartbeat detection and EM artifact for all the 48 records: (a) SE and SNR; (b) PP and SNR.

As shown by Figures 4.9 to 4.11, the signals contaminated with BW, MA and EM artifacts degraded the detection performance of the Pan Tompkins, Hamilton and WQRS algorithms. The analysis on the 48 records from the MIT-BIH Databases showed that the noisy signal decreased the heartbeat detection performance, with low average SE and PP at the lowest SNR compared to the average detection in clean ECG signals (Figure 4.1.). The average detection performance showed the highest influence by MA and EM artifacts, with the sensitive WQRS algorithm being most affected by the noisy signal.

4.4. Discussion

In this study, the relationship between the ECG noise and heartbeat detection for ambulatory cardiac monitoring was investigated using heartbeat detection algorithms for both clean and noise-simulated ECG signals contaminated with BW, MA and EM artifacts. There was no significant difference found in the performance of the heartbeat detection algorithms when the clean signal was used. The beat detector was able to handle the high-quality signals from the MIT-BIH database that had dynamic signal due to the abnormal beats, noise and artifacts effects.

The experimental results on noisy signal showed valid heartbeat detection performance. The findings implied that signals contaminated with noise and artifacts degraded the ECG morphology and decreased the potential of heartbeat detection in the ambulatory signal. This was represented by the relationship between the noise types and the level of SNR intensity, and confirmed by the performance of the average SE and PP of the algorithms used in the experiments. Based on the results, none of the algorithms was able to detect all the QRS complexes without any false positive and false negative at the highest level of noise, indicating the weakness of the Pan Tompkins, the WQRS and the Hamilton algorithms. The Pan Tompkins algorithm showed the best performance of detection when dealing with noisy signals, followed by the Hamilton algorithm while the WQRS algorithm showed the poorest performance.

The relationship between the characteristics of ECG noises and the heartbeat detection indicated that the BW had a lesser influence on the heartbeat detection performance except with the more sensitive WQRS algorithm. Meanwhile, the EM artifacts had the highest influence on the detection algorithm, followed by MA and BW. Higher interferences that degraded the detection performance were mainly due to MA and EM artifacts. The higher intensity of MA and EM artifacts contributed to the false positive and false negative values that affected the percentage of QRS complexes detected. However, the EM artifacts contributed to the poorest detection performance which was proven by the lower performance of SE and PP in the high noise signal and the distorted ECG morphology, leading to the highest number of misdetections and false detections. Further improvements should consider the effects of MA and EM artifacts in ECG signals to deal with the false detection of the QRS complex in order to improve the detection performance.

4.5. Summary

This chapter presented the methodology to analyse the effects of noise from ambulatory recording on heartbeat detection performance. Dissimilar to the previous studies [18, 42-43], the methodology used in this chapter clearly examined the noise types and intensity level of noise that affected the heartbeat detection performance. The research data in this chapter were drawn from ambulatory ECG signal and noise sources from ambulatory recording. This chapter also showed the effects of high noise in the detection performance. The performance of threshold-based detection method was evaluated using three different noise sources from ambulatory environment, and the results indicated that they needed improvement to perform. Based on the results, the effects of noisy ECG signal might lead to the highest number of misdetections and false detections during the heartbeat detection process. Thus, further improvement and method to deal with this problem will be discussed in the next chapter.

Chapter 5
Noise-Tolerant Heartbeat Detection Method

5.1. Introduction

In Chapter 4, the effects of noisy signal on the threshold-based heartbeat detection performance were evaluated. As a result, it was found that false detection from MA and EM artifact was affecting the QRS detection performance. In addition, the Pan Tompkins algorithm [9] performed better compared with other algorithms. In the literature, the Pan Tompkins algorithm has also been used in most arrhythmia heartbeat classification system [6, 7, 30]. It has been proven to achieve good detection accuracy in clean ECG signals. However, the performance of Pan Tompkins algorithm was affected by the noisy ECG signal especially with EM and MA noise.

Researchers have suggested many methods of noise reduction to deal with noisy signal and detect QRS complexes [44-47]. Many works have filtered the signal first to increase the robustness [9-10, 47]. Nonetheless, filtering does not work for EM and MA noises. According to a study [48], periodical property of ECG is able to improve the QRS detection in ECG signal with motion artifacts. Thus, autocorrelation technique has been investigated in this study. In a previous study [44], the short auto-autocorrelation with template matching has been proposed for noisy ECG signals. However, the template matching was computationally expensive because of the sample-by-sample moving with the template along the ECG signals.

Therefore, in this chapter the noise-tolerant heartbeat detection method was proposed. The proposed method modified the Pan Tompkins algorithm by using the autocorrelation technique in this work. In contrast to a study [44] that used template matching in their work, the threshold-based detection method was employed at the last stage in this study since the autocorrelation could also produce error assumption when dealing with high noise. To solve this issue, the Savitzky-Golay moving average (SGMA) technique [49] was used. The SGMA is a smoothing technique that modifies the data points of the signal and reduces the noises and spikes in the signal. Three main experiments were performed to evaluate the proposed method: using the standard database, ECG-Noise simulated signal and the actual GUDB data. The results of the proposed method are presented in this chapter.

5.2. Proposed Heartbeat Detection Method

Figure 5.1 shows the block diagram of the proposed heartbeat detection method and Figure 5.2 shows the output of each steps in the proposed method. The proposed work consisted of two main stages: processing and QRS detection with six steps, including a band-pass filter, derivative, squared, Savitzky-Golay moving average, autocorrelation and adaptive threshold.

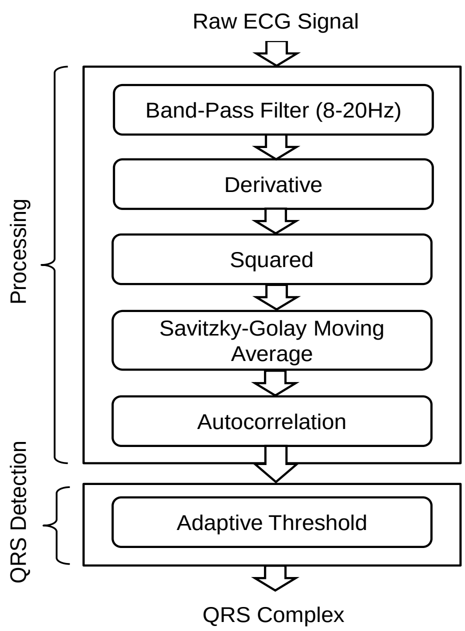


Figure 5.1. Block diagram of the proposed heartbeat detection method.

Firstly, in order to attenuate the noise, the signal passed through a digital band-pass filter composed of cascaded high-pass and low-pass filters. The next process after filtering was differentiation, followed by squaring, SGMA integration and autocorrelation. The information above the slope of QRS was obtained in the derivative steps. The acquiring process intensified the slope of the frequency response curve of the derivative and helped restrict false positives caused by T waves with higher than usual energies. The SGMA produced a smoothing signal that included information about both the slope and width of the QRS complex. From the smoothing signal, the fiducial point was identified and refined using autocorrelation. Then, the location of the QRS complex was determined after using the adaptive threshold. All the steps in the proposed heartbeat detection are described below.

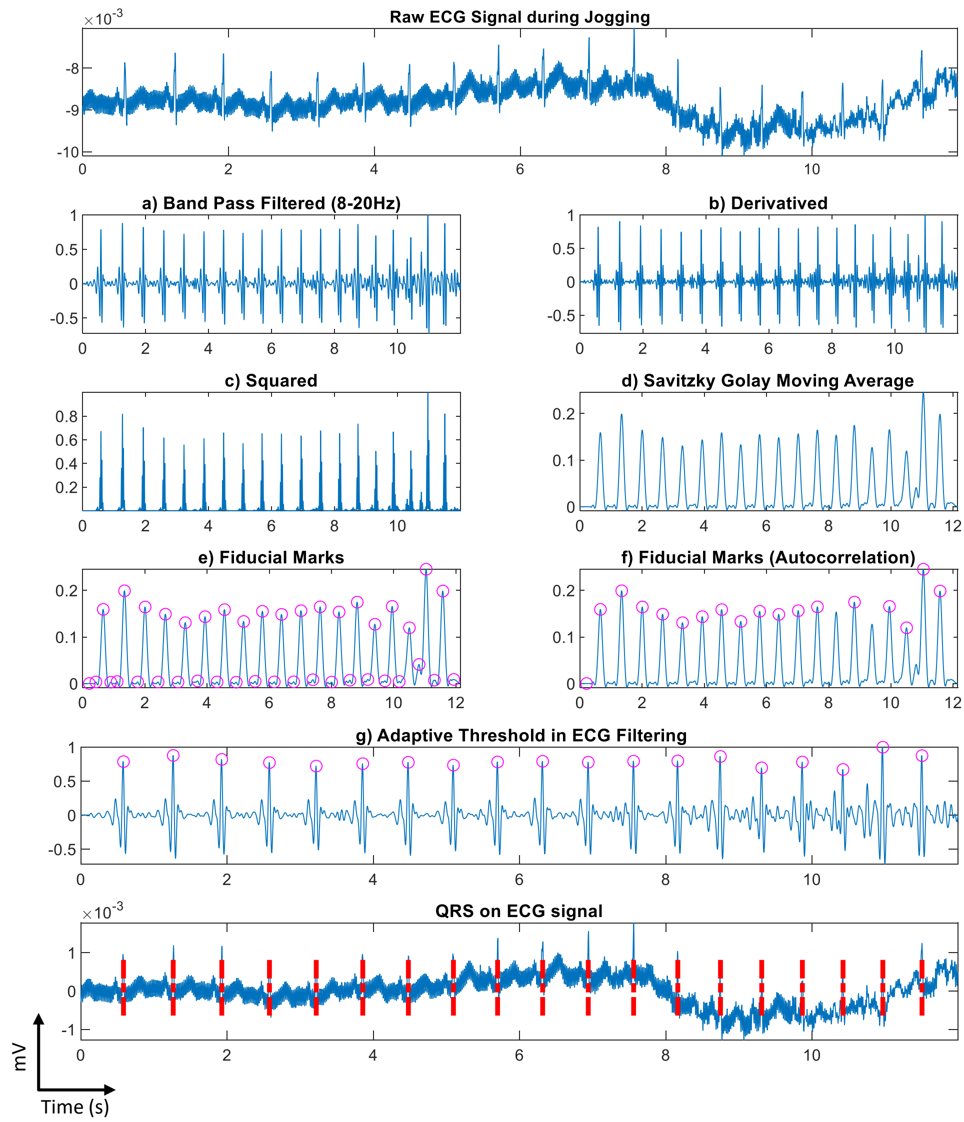


Figure 5.2. The output of each steps in the proposed heartbeat detection method with ECG signal during jogging.

5.2.1. ECG Processing

The purpose of this stage was to filter the noise and construct the fiducial points of QRS peak. Five steps were employed in the processing stages as described below. In general, the overall processing stages could be divided into five steps: (1) Filtering, (2) Derivative, (3) Squaring, (4) Savitzky-Golay moving average, (5) Autocorrelation.

5.2.1.1. Band-Pass Filter

Morphologies of normal and abnormal QRS complexes differ widely. The ECG signal is often corrupted by noise from many sources as discussed. Therefore, band-pass filtering is an essential first step for nearly all QRS detection algorithms. The purpose of band-pass filtering is to remove the baseline wander and high frequencies, and to suppress the P and T waves that do not contribute to detect the QRS complexes. It offers good transition-band characteristics at low coefficient orders, making it efficient to implement [29]. In this study, the band-pass filter used a third-order Butterworth filter with the passband of approximately 8-20 Hz to maximize the QRS energy. The band-pass filter was designed using the cascaded low-pass and high-pass filters. The output of the band-pass filter is shown in Figure 5.2(a).

5.2.1.2. Derivative

After the filtering process, the signal is differentiated to provide the QRS complex slope information. The QRS complex slope is produced using a derivative process to gain high-frequency slopes in the signal and suppress the low frequency of P and T waves. The output of the derivative is shown in Figure 5.2(b).

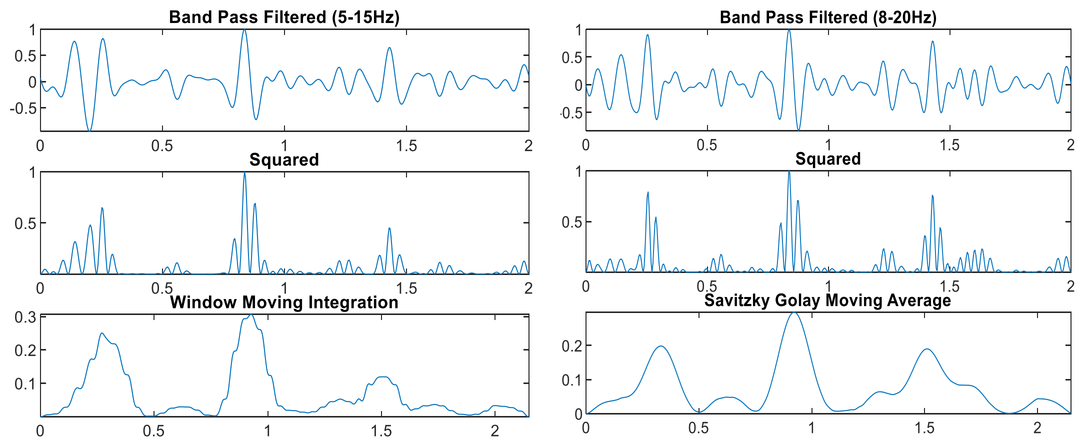
5.2.1.3. Squared

From the derivative process, the signal was squared point by point to enhance large values and boost high-frequency components. This techniques performing nonlinear amplification of the output of derivative and emphasizing the higher frequencies of QRS peak or predominantly the ECG frequencies. The output of the derivative is shown in

Figure 5.2(c).

5.2.1.4. Savitzky-Golay Moving Average (SGMA)

A Savitzky-Golay Moving Average [49, 85] is generally used to smoothen the signal to increase the precision of the data without distorting the signal tendency. It uses the convolution process by fitting the data point with low degree polynomial by the method of linear least square. SGMA performs better in some applications than the standard averaging FIR filters [86], which tend to filter high-frequency content along with the noise as shown in Figure 5.3. The SGMA is generally designed with frame size and fitting order as they are the basic conditions of this technique. The frame size and the order of the SGMA determine the cutoff characteristics of the signal spectra. It is a challenging task to evaluate the optimal conditions of the frame size and order for SGMA in the signal filtering because there is no direct relation of order and frame size of this technique, with cutoff frequency, empirical or checks and trial method possible to be applied.



(a) (b)

Figure 5.3. Comparison of signal output window moving integration in (a) Pan Tompkins and (b) SGMA.

After investigating the best parameters for SGMA that reflect the basis of heartbeat, 0.3s was used as the frame length, considering the widest possible QRS complex with 6 as the polynomial order. For the frequency sampling, 360 Hz was used, with about 109 samples in an odd number needed for frame length. From the squared signal, the SGMA was employed by using *sgolayfilt* MATLAB function. Then, the signal was integrated to obtain the slope of the R wave. The output of the SGMA is shown in Figure 5.2(d).

5.2.1.5. Autocorrelation

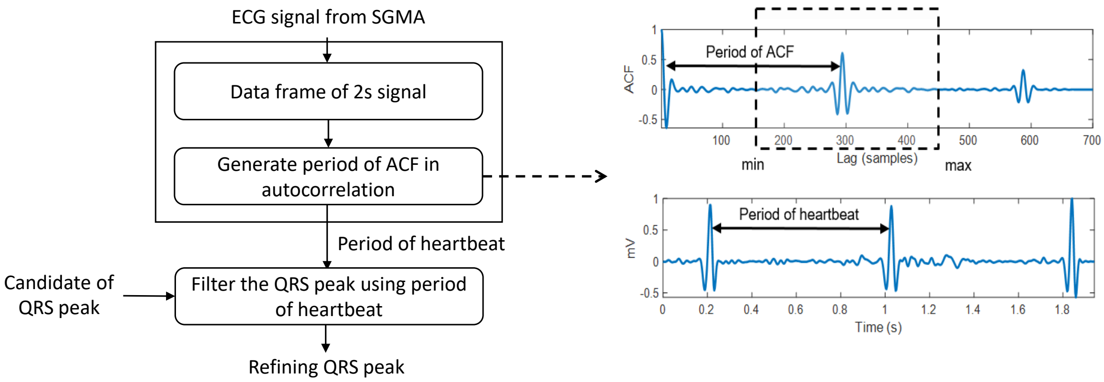
Autocorrelation is the cross-correlation of a signal with a delayed copy of itself [44, 48, 86]. It is defined mathematically as the convolution between the same signals, which are the signal and its shifted version with fixed step size [66]. The autocorrelation is useful for finding repeating patterns, such as the presence of a periodic signal within a continued signal. By using the periodic of the waveforms, it can be automatically suppressing the periodic noise in the signals and providing the estimation of heartbeat period. In the autocorrelation output, a narrow peak is the identification of a peak that can be thrown off by the presence of low amplitude and periodic noise. Therefore, the autocorrelation output can be used to identify present components and determine the peak position. The autocorrelation function (ACF) is defined as follows:

$$R_y(k) = \sum_{n=-\infty}^{n=\infty} y(n) \times y(n-k) \tag{5.1}$$

where R_y is the autocorrelation function, $y(n)$ is the ECG signal, k is the number of lags of the autocorrelation and n is the total number of sample points in the data frame [66].

Figure 5.4 (a) shows the block diagram of these steps. The first process in this step was to identify the candidate QRS fiducial points from the SGMA signal as shown in Figure 5.2(e). Each fiducial point was considered as a potential QRS. To reduce the possibility of incorrectly selecting a noise peak as a QRS, each peak was refined using the period of heartbeat by autocorrelation. One complete data frame of 700 samples of the signals from SGMA was taken at a time as the input of AFC. The AFC was applied on the data frame and the duration of periodic of signal was calculated as the output.

The distance between the first narrow peak of the ACF output and the origin center was defined as the period of ACF as shown in Figure 5.4 (b).The distance (number of sample points) between the peak location and the origin center was calculated to produce the period of ACF. Then, the period of heartbeat was used to filter the candidate QRS fiducial points. The output of these steps was the refined QRS fiducial points as shown in Figure 5.2 (f).



(a) (b)

Figure 5.4. Block diagram of the steps in autocorrelation stage.

5.2.2. QRS Detection

When the processing was completed, the following step in this stage was to determine the candidate peaks as the QRS complex by using the adaptive threshold. The calculation of adaptive threshold was adopted from the Pan Tompkins algorithm [9]. In this stage, two sets of thresholds were used to detect the QRS complexes. One set limited the filtered ECG, and the other limited the signal produced by SGMA. By using thresholds on both signals, the reliability of detection was improved compared to using waveform alone. Low threshold was possible because of the improvement of the SNR by the band-pass filter. The higher of the two thresholds in each of the two sets was used for the first analysis of the signal. The lower threshold was used if no QRS was detected in a certain time interval so that the search-back technique was necessary to look back in time for the QRS complex.

5.2.3. Steps of the Proposed Method

Input raw ECG signal, $f(t)$ is filtering using the third order Butterworth filter with the passband of approximately 8-20 Hz. After the filtering, the signal, $x(n)$ is differentiated to provide slope information using the difference Equation 5.2,

$$q[n] = \frac{1}{8}(-x[n-2] - 2x[n-1] + 2x[n+1] + x[n+2]) \tag{5.2}$$

After differentiation, the signal is squared point by point using the Equation 5.3,

$$y[n] = (q[n])^2 \tag{5.3}$$

This make all data points positive and derivative emphasizing the higher frequencies or predominantly the ECG frequencies.

Then the derivative signal was smoothing using the SGMA technique by the Equation 5.4,

$$y_t = \frac{1}{2k+1}(y_{t-k} + y_{t-k+1} + \cdots + y_{t+k-1} + y_{t+k}) \tag{5.4}$$

where y_t is SGMA or smoothing signal $t = k+1, k+2, \ldots, n-k$. From the smoothing signal, the candidate of QRS fiducial point was identified. On the other hand, after the smoothing, the signal was divide into 700 samples or 0.2 second each frame and the autocorrelation function was applied on the data frame by using Equation 5.5,

$$R_y(L) = \sum_{n=0}^{N} y(n) \times y(n-L) \tag{5.5}$$

where R_y is the autocorrelation function, $y(n)$ is the SGMA signal, L is the number of positive lags of the autocorrelation, and N is the total number of sample points in the data frame.

Then the peak in the R_y was searched within the max heart rate of 120 bpm based on the calculation of heartbeat rate per minute (bpm) as Equation 5.6 as follows:

$$heart\_rate = \frac{60 \times fs}{120} \tag{5.6}$$

where fs is the sampling frequency. The max heart rate is taken because the normal human heart rate always lies between range of 50 bpm and 120 bpm [24]. The distance between the peak and the origin center was calculated to find the period of ACF. Then the candidate of QRS fiducial points was refined using the period of heartbeat to produce a set of refining QRS peak.

Then, the refining of QRS peak was filtered using the adaptive threshold. Two sets of adaptive threshold was applied using the filtering and smoothing signal. The set of thresholds initially applied to the SGMA signal was computed from Equation 5.7.

$$Threshold_1 = NoiseLevel_1 + 0.25 \ (SignalLevel_1 - NoiseLevel_1) \tag{5.7}$$

where all the variables refer to the SGMA waveform with $NoiseLevel_1$ being the running estimate of the noise peak, $SignalLevel_1$ being the running estimate of the signal peak, and $Threshold_1$ being the first threshold applied.

The threshold was automatically updated after detecting a new peak based on its classification as a signal or noise peak from Equation 5.8 and 5.9.

$$\begin{gathered} SignalLevel_1 = 0.125PEAK_1 + 0.875SignalLevel_1, \\ if \ \ PEAK1 \ \ is \ \ signal \ \ peak \end{gathered} \tag{5.8}$$

$$\begin{gathered} NoiseLevel_1 = 0.125PEAK_1 + 0.875SignalLevel_1, \\ if \ \ PEAK1 \ \ is \ \ noise \ \ peak \end{gathered} \tag{5.9}$$

where $PEAK1$ is the new peak found in the SGMA signal. At the beginning of the QRS detection, a 2-second learning phase was needed to initialize $SignalLevel_1$ and $NoiseLevel_1$ as a percentage of the maximum and average amplitude of the SGMA signal, respectively.

If a new $PEAK1$ was under the $Threshold_1$, the noise level was updated. If $PEAK1$ was above the $Threshold_1$, the algorithm implemented a further check before confirming the peak as a true QRS, taking into consideration the information provided by the band-pass filtered signal. In the filtered signal, the peak corresponding to the one evaluated on the SGMA signal was searched and compared with a threshold, calculated in a similar way to the previous step as Equation 5.10.

$$Threshold_2 = NoiseLevel_2 + 0.25 \ (SignalLevel_2 - NoiseLevel_2) \qquad (5.10)$$

where all the variables refer to the filtered signal with $Threshold_2$ being the second threshold applied.

5.3. Performance Evaluation

The proposed method was aimed to improve the detection of QRS complex in highly noisy ECG signal. In this section, the performance results of the proposed method are presented. Firstly, the performance of the proposed method is evaluated with the standard ambulatory ECG signal to observe the performance in clean signal and arrhythmia beats. Then, the performance results of the proposed method are compared with other heartbeat detection algorithms results. To investigate the performance with noisy signal, two types of data have been tested in this study. The ECG-noise simulated signal and real ECG signal from the GUDB database are used as an evaluation. The performance results and analysis are described in the next section.

5.3.1. Evaluation with the Standard Ambulatory ECG Signal

Table 5.1 presents the performance of the proposed method on 48 records from MIT-BIH with the lower and higher accuracy of 93.75% and 100%. As explained in Section 3.1.1.1, the records in MIT-BIH could be categorized into two groups: the first group included 23 records (record number 100 to 124) that were randomly chosen containing few arrhythmias types and noise from ambulatory environment; the second group included 25 records (record number 200-234) with examples of uncommon but clinically important arrhythmias that would not be well represented in a small random sample.

Table 5.1. Performance evaluation of the proposed method with MIT-BIH.

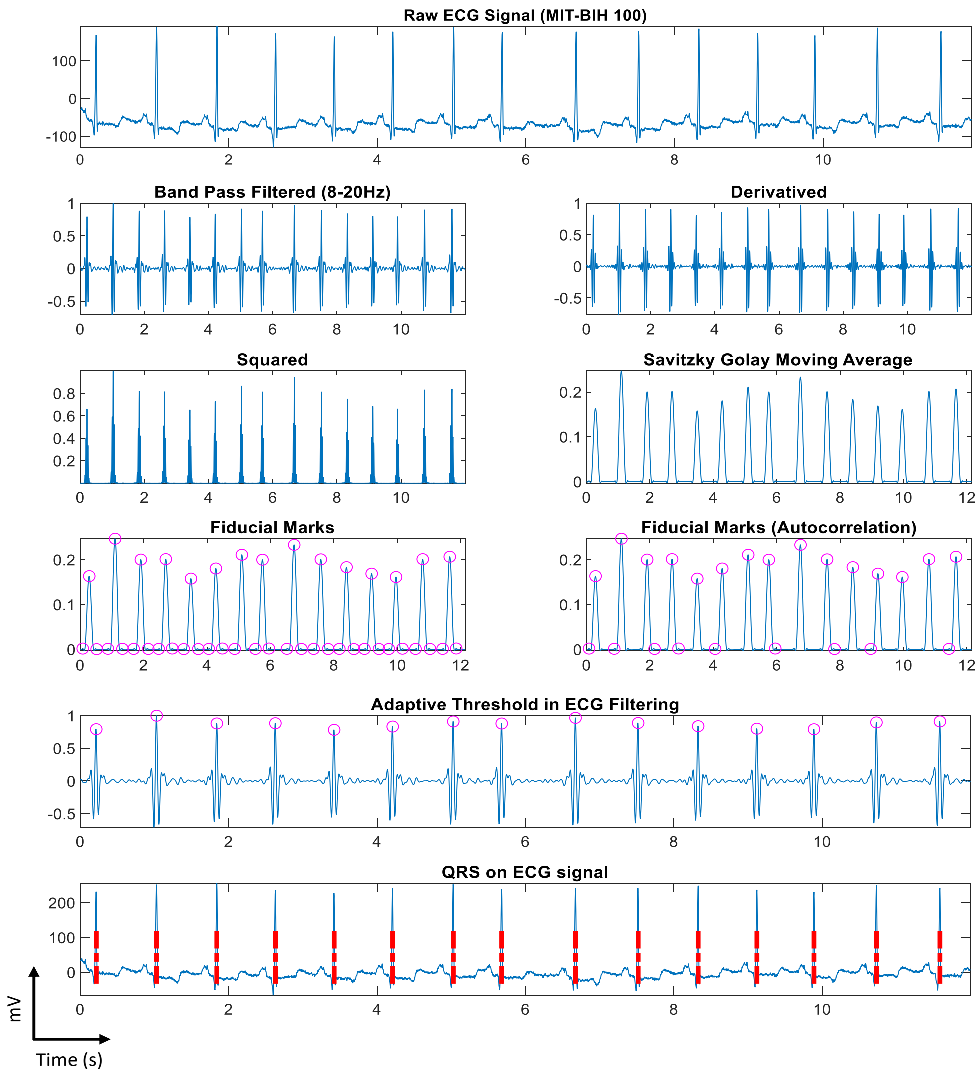
Records	SE (%)	PP (%)	ACC (%)	Records	SE (%)	PP (%)	ACC (%)
100	100.00	100.00	100.00	201	99.42	99.96	99.69
101	99.95	99.79	99.87	202	92.21	100.00	96.11
102	99.77	99.95	99.86	203	93.82	100.00	96.91
103	99.95	100.00	99.98	205	87.99	99.51	93.75
104	99.37	99.51	99.44	207	99.13	100.00	99.57
105	99.07	99.30	99.19	208	95.00	99.83	97.42
106	95.31	100.00	97.66	209	92.35	99.74	96.05
107	99.77	99.86	99.82	210	96.97	100.00	98.49
108	98.53	98.86	98.70	212	96.49	99.96	98.23
109	99.80	100.00	99.90	213	99.96	100.00	99.98
111	99.95	100.00	99.98	214	99.51	99.97	99.74
112	100.00	100.00	100.00	215	97.83	99.91	98.87
113	99.89	100.00	99.95	217	99.64	100.00	99.82
114	99.31	100.00	99.66	219	99.46	99.91	99.69
115	100.00	100.00	100.00	220	98.00	100.00	99.00
116	99.05	99.83	99.44	221	99.32	100.00	99.66
117	100.00	100.00	100.00	222	98.60	100.00	99.30
118	99.96	100.00	99.98	223	94.08	100.00	97.04
119	98.84	99.39	99.12	228	99.73	100.00	99.87
121	99.95	100.00	99.98	230	99.27	99.46	99.37
122	100.00	100.00	100.00	231	99.96	100.00	99.98
123	99.47	100.00	99.74	232	100.00	100.00	100.00
124	98.95	100.00	99.48	233	98.93	99.94	99.44
200	100.00	100.00	100.00	234	95.58	100.00	97.79
			Worst		87.99	98.86	93.75
			Best		100.00	100.00	100.00
			Average		98.33	99.89	99.11

The proposed method performed well in the first group, detecting the QRS complex in noisy signal that contained arrhythmia beats except record 108 with 98.70% accuracy. Record 108 was one of the most difficult records in MIT-BIH and it was despoiled by low amplitude that degraded the detection performance. In the second group, the results showed that almost all records performed higher percentage of PP. However, the number of misdetections in some records in the second group were higher, contributing to decreased SE percentage, such as record 202, 203, 205 and 209 with 92.21%, 93.82%, 87.99% and 92.35% of SE, respectively. The signal from record 202, 203 and 205 indicated a combination of normal beat with almost all arrhythmias beats and fusion of beats while the signal from the record 209 was a combination of normal and supraventricular and ventricular beats. It was observed that this signal was dynamic due to the abnormal beats, contributing to the effects of the periodic morphological signal, and degrading the performance of the proposed method. Figure 5.5 visualizes the output of clean and noisy signal and Figure 5.6 shows the output of arrhythmias beat in the signal produced by the proposed method.

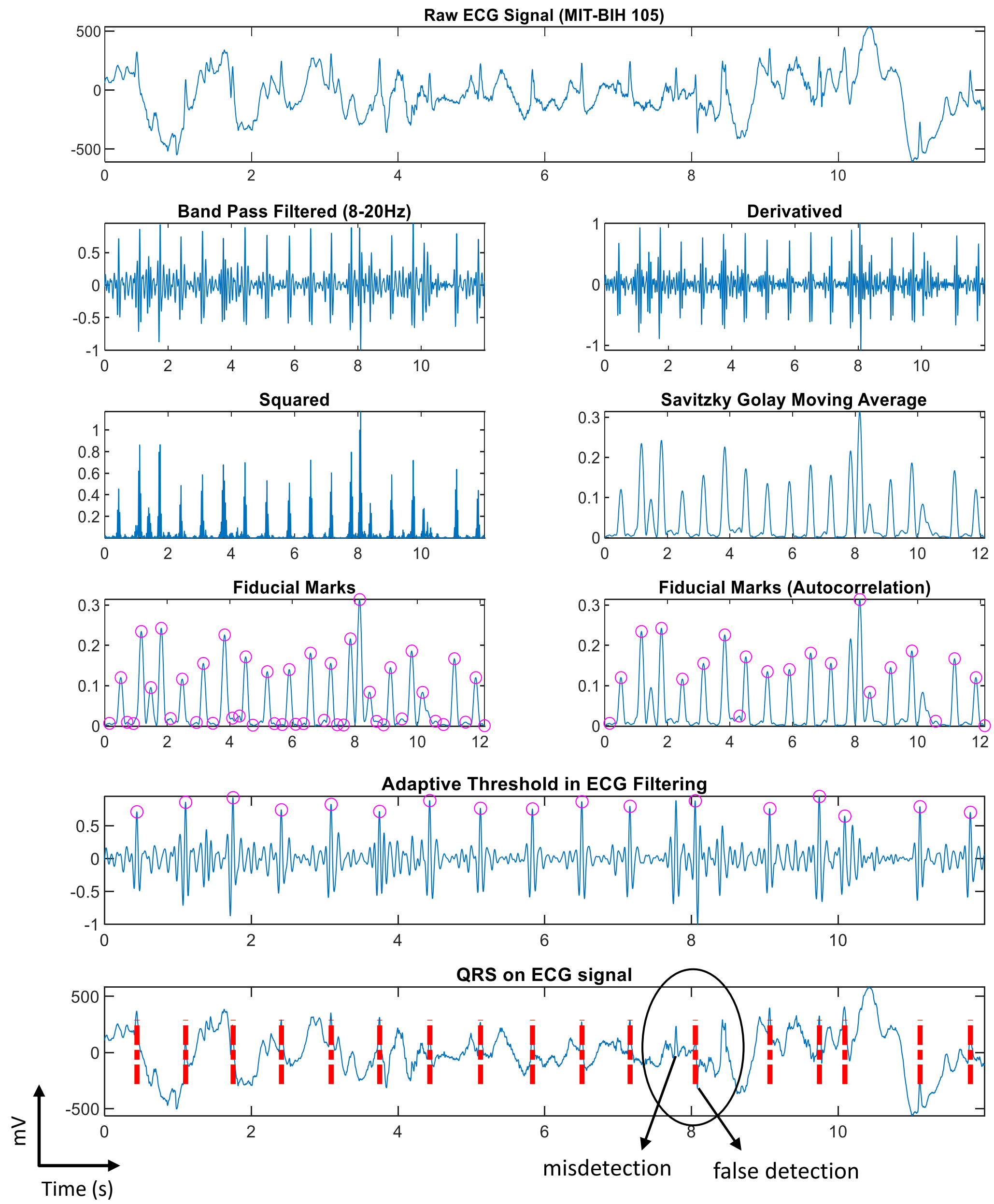
Table 5.2 shows the accuracy comparison of the proposed method with other heartbeat detection algorithms. Four algorithms were selected for comparison: the Pan Tompkins [9], Hamilton [10], WQRS [11] and Nakai [44] algorithms. The first three algorithms have been investigated and described in the previous chapter while the Nakai algorithm was selected because their work has also been tested in highly noisy signal. Considering the effects of noise tolerance in the detection, the proposed method performed better with 99.11% than Nakai algorithm (92.48%). It was observed that the signals contained dynamic arrhythmias beats such as the signal in the second group that affected the performance of the heartbeat detection method with the noise-tolerant approach. Comparing the results from Pan Tompkins, Hamilton and WQRS algorithms that were sensitive to noisy signal, the overall accuracy of the proposed method was still acceptable.

Table 5.2. Comparison of the proposed beat detection performance with other detection algorithms.

Methods	Average (%)		
	1st Group (Record 1-124)	2nd Group (Record 200-234)	All Records
Pan Tompkins [9]	99.43	99.66	99.55
Hamilton [10]	99.08	99.19	98.65
WQRS [11]	98.08	99.18	99.13
Nakai [47]	95.60	89.18	92.48
Proposed	99.64	98.62	99.11

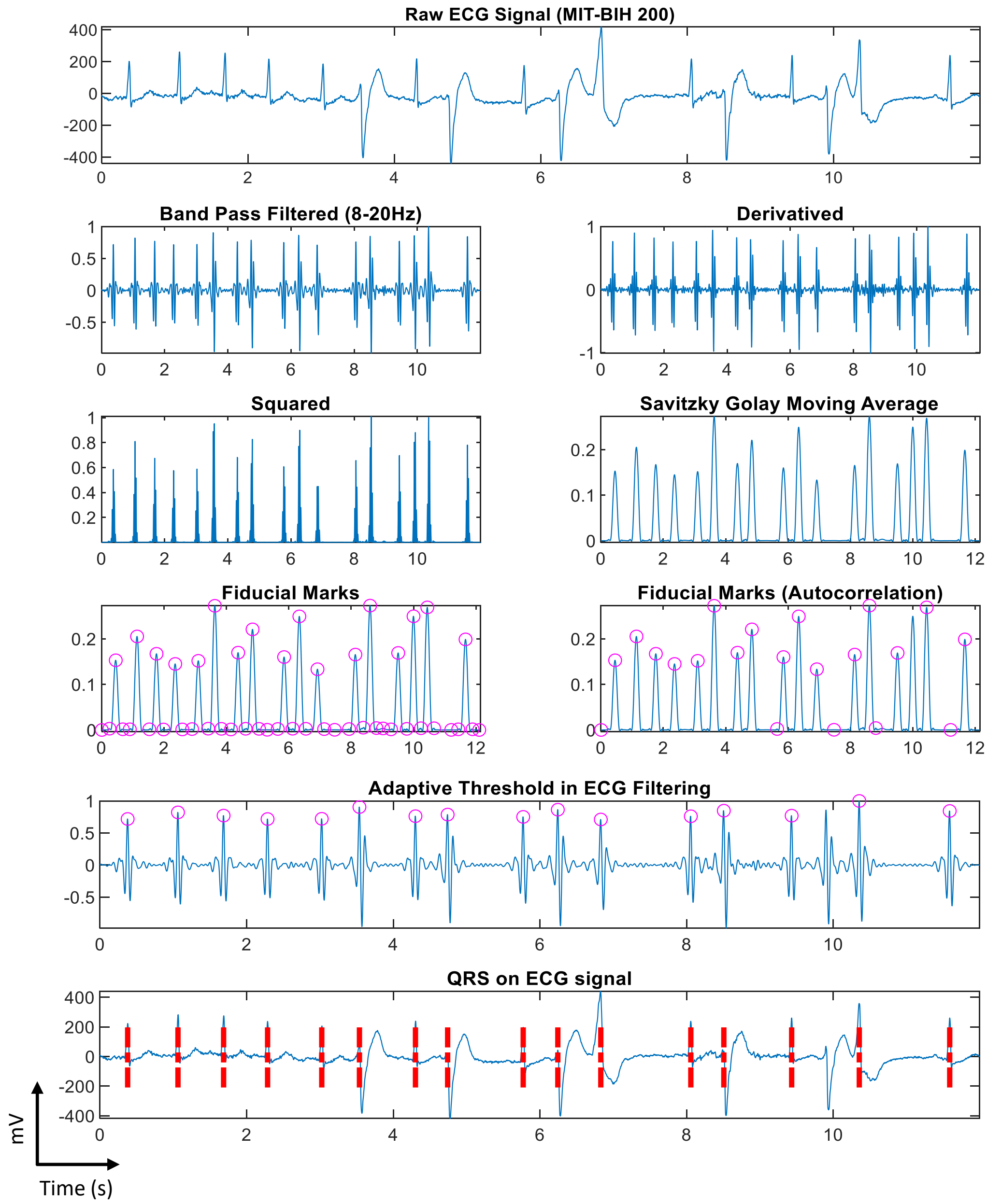


(a) Output from Record number 100

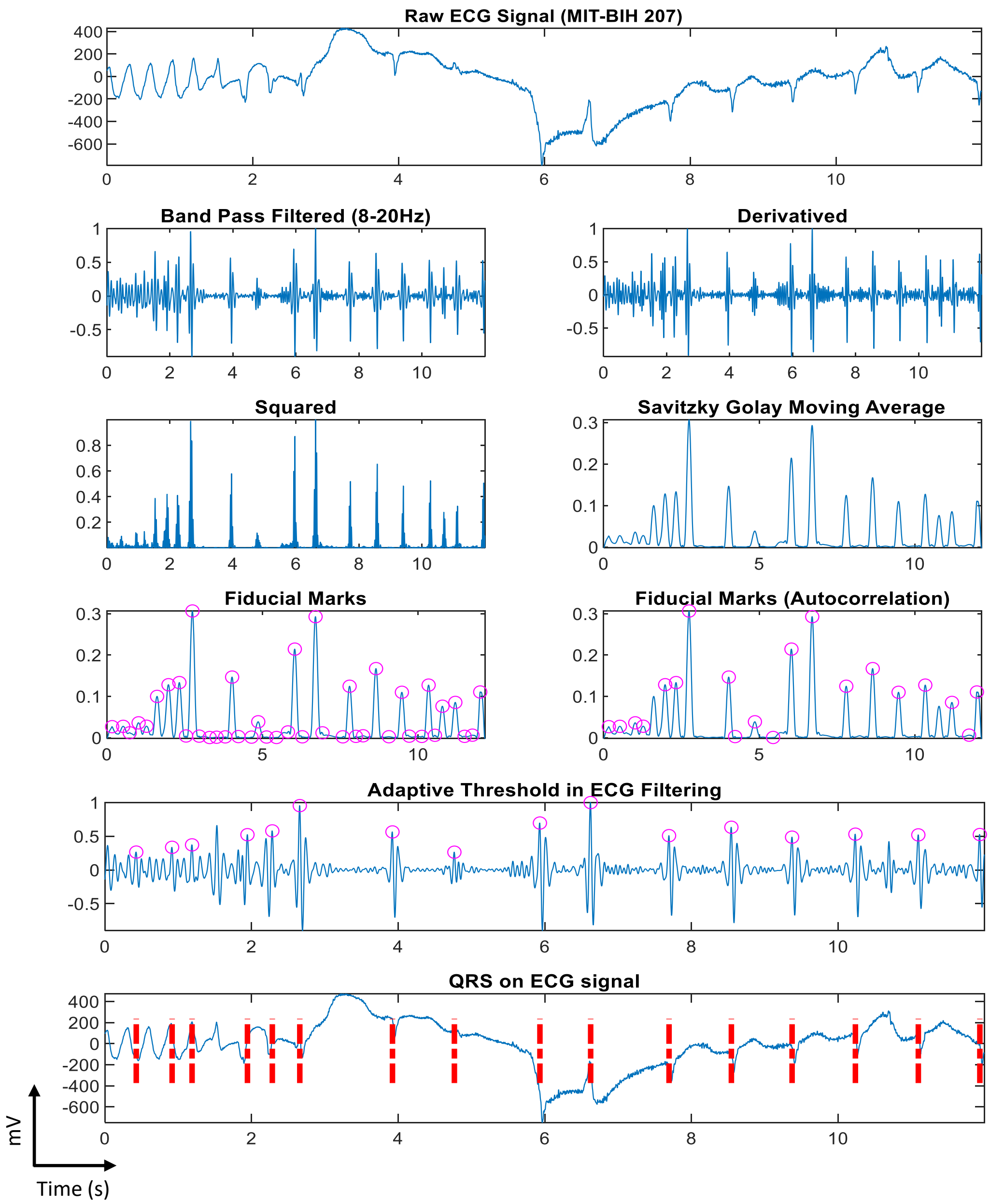


(b) Output from Record number 105

Figure 5.5. Output of proposed method in (a) clean signal and (b) noisy signal of MIT-BIH.



(a) Output from Record number 200



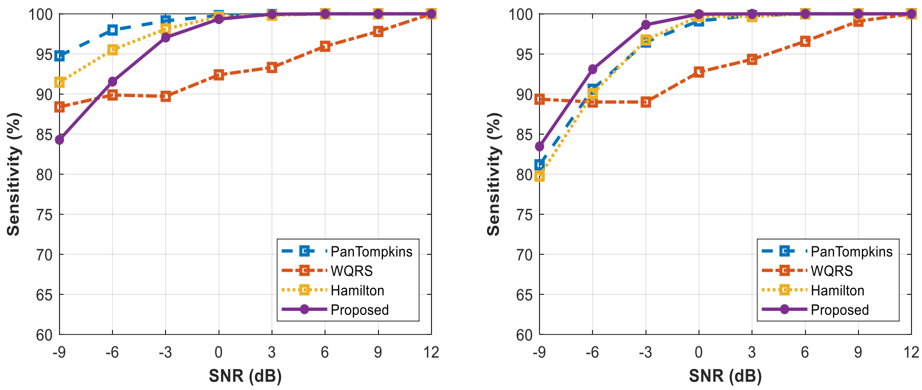
(b) Output from Record number 207

Figure 5.6. Output of proposed method in (a) signal with combination of ventricular beats and (b) signal with predominant rhythm of abnormal beats.

5.3.2. Evaluation with Noisy ECG Signal

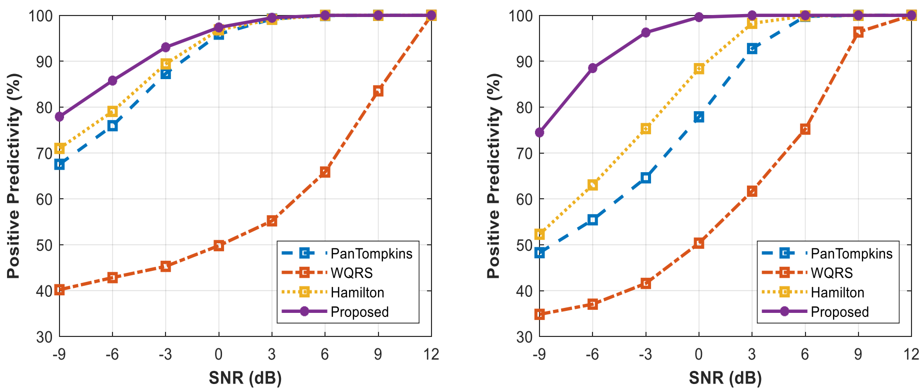
Figures 5.7 to 5.9 show the relationship between the noise intensity and the performance of SE, PP and DER percentage. The MIT-BIH record 100 was used to evaluate the effects of noise contamination MA and EM source. Figure 5.7(a), 5.8(a) and 5.9(b) present the performance comparison with MA noises. As shown in Figure 5.7(a), the results of the proposed method with MA decreased the SE at lower SNR compared with the other algorithms with 84.29 % at -9 dB. Although the proposed method had decreased the SE, it resulted in a higher PP as the number of false detections decreased with noise intensity level (Figure 5.8(a)). The performance of the proposed method on MA noise is shown in Figure 5.9(a). From the figure, the DER showed that the proposed method was better than the other algorithms by producing lower error detection under all conditions of SNR. At the lower SNR, MA of -9 dB, the proposed method achieved 31.96% of DER compared with 33.41%, 33.41% and 61.81% for the Pan Tompkins, Hamilton and WQRS algorithms, respectively.

Figure 5.7(b), 5.8(b) and 5.9(b) show a performance comparison with the EM noise. As shown in Figure 5.7(b), the proposed method performed better in the EM noise with 83.46% of SE compared to the other algorithms with 81.17%, 79.76% for the Pan Tompkins and Hamilton algorithm, excluding the WQRS algorithm which obtained 89.35% at SNR of -9 dB. There was a similar trend for PP in Figure 5.8(b), in which in all conditions of noise, the proposed method showed a good result, with rapidly decreasing false detections that increased the PP percentage. The results demonstrated that the proposed method was able to reduce the number of false detections in lower EM noise, SNR of -9 dB, with 74.48% of PP compared to 48.27%, 52.29% and 34.84% for the Pan Tompkins, Hamilton and WQRS algorithms, respectively. This led to the improvement of the results of DER as shown in Figure 5.9(b) in which the proposed method managed to reduce the noise with 33.98% at low intensity level of EM at -9 dB. Based on the results with EM and MA noise, in general, the proposed method improved the noise tolerance compared to the other algorithms when ECG was contaminated by both MA and EM noise as resulted of DER. These results also showed that the proposed method performed better in EM noise compared to MA noise to detect the QRS complexes. Figure 5.10 visualizes the output of clean and noisy signal.



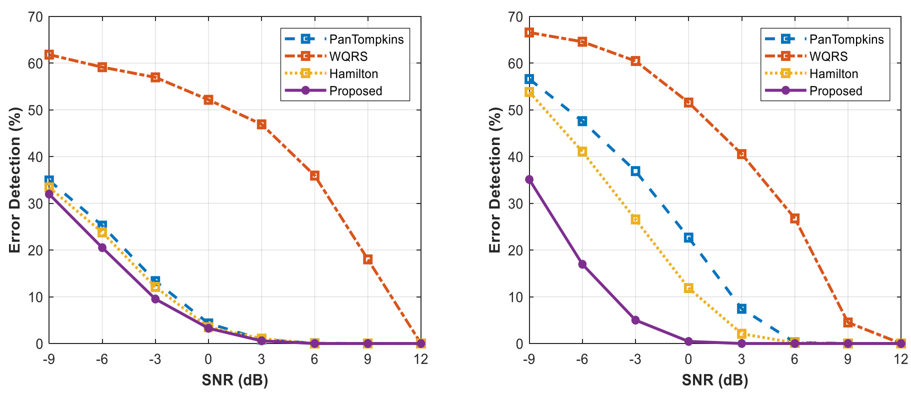
(a) (b)

Figure 5.7. Comparison of the SE with ECG-Noise simulated Signal for record 100: (a) MA; (b) EM.



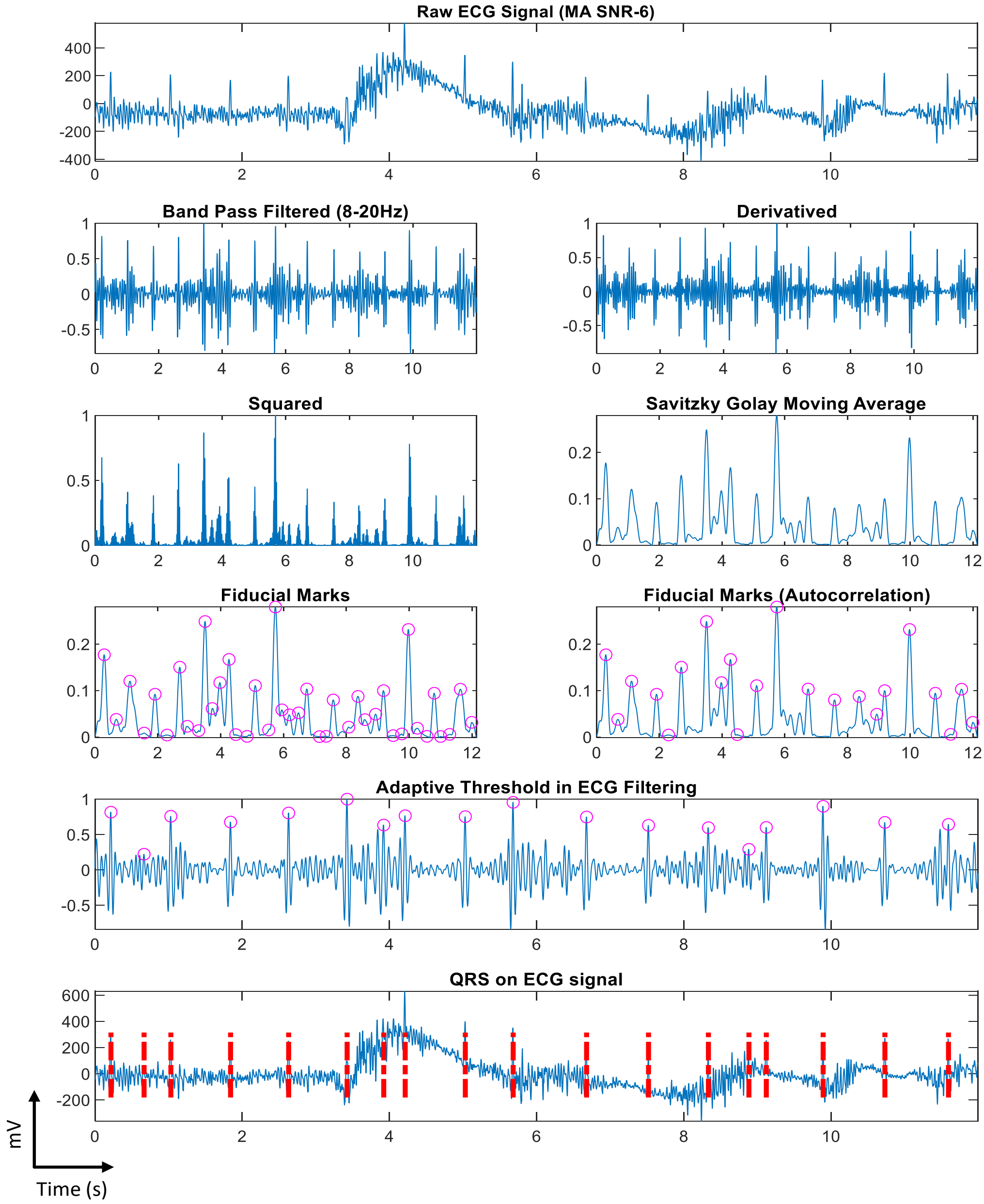
(a) (b)

Figure 5.8. Comparison of the PP with ECG-Noise simulated Signal for record 100: (a) MA; (b) EM.

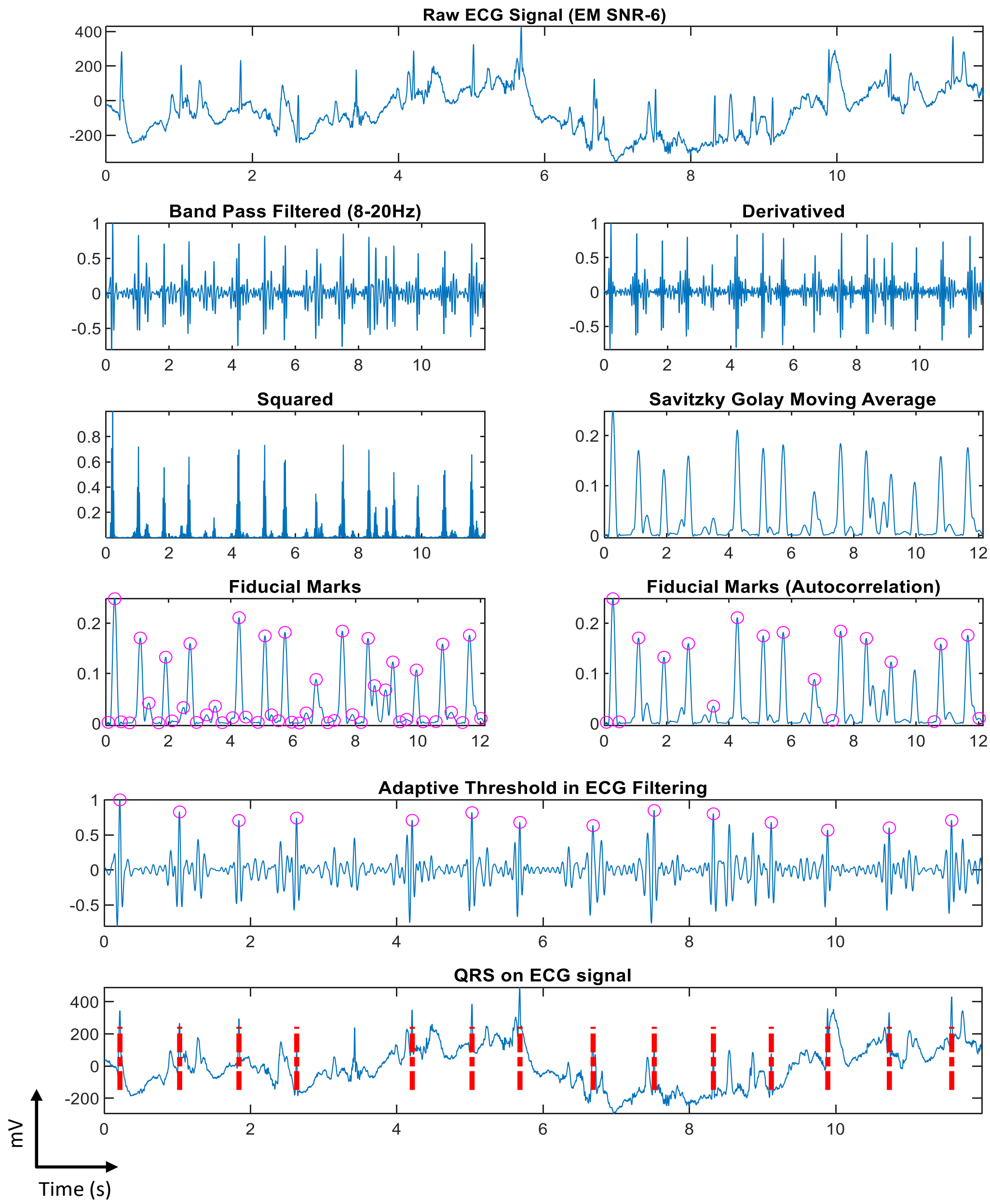


(a) (b)

Figure 5.9. Comparison of the DER with ECG-Noise simulated Signal for record 100: (a) MA; (b) EM.



(a) Output from Record number 100



(b) Output from Record number 105

Figure 5.10. Output of proposed method in ECG-Noise simulate signal with SNR -6 dB of (a) MA and (b) EM noise.

5.3.3. Evaluation with Real Data

Next, the proposed method was evaluated using an ECG signal obtained using a wearable ECG monitoring device and stored in GUDB database as described in section 3.1.3. Figure 5.11 and Table 5.3 presents the performance results of the proposed method and comparison with the other algorithms on the signal from GUDB database. The aim of this experiment is to evaluate the performance of proposed method during different activities with actual data collecting from exercise activities. The proposed method was tested with two-minutes ECG signals collected from nine subjects during three different activities: siting, walking and running on a treadmill. As a result, the performance of the proposed method was lower with the increase level of activity, especially during running with the increasing DER percentage as shown in Figure 5.11. However, the proposed method able to detect the heartbeat in actual data and show good results with an average DER of 0.00%, 0.07% and 2.39% for sitting, walking and running compared with the other methods.

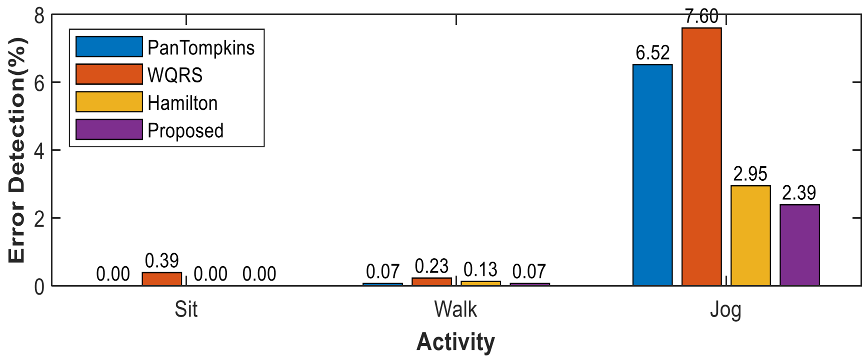


Figure 5.11. Comparison of the average of error detection performance during different activity with actual data.

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Table 5.3. Comparison of the beat detection methods performance with GUDB data.

Subject	Activity	Pan Tompkins [9]			WQRS [11]			Hamilton [10]			This Study		
		SE (%)	PP (%)	DER (%)	SE (%)	PP (%)	DER (%)	SE (%)	PP (%)	DER (%)	SE (%)	PP (%)	DER (%)
Subject 1	Sit	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Walk	100.00	99.40	0.60	100.00	100.00	0.00	100.00	98.80	1.20	100.00	100.00	0.00
	Run	98.02	96.88	4.98	93.28	97.93	8.53	94.86	97.56	7.34	98.42	98.42	3.11
Subject 2	Sit	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Walk	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	99.40	100.00	0.60
	Run	99.20	99.60	1.20	99.60	99.20	1.20	99.20	100.00	0.80	99.60	100.00	0.40
Subject 3	Sit	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Walk	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Run	88.64	83.27	24.76	97.73	76.11	25.22	95.83	95.11	8.66	93.54	93.89	11.83
Subject 4	Sit	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Walk	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Run	98.03	100.00	1.97	99.01	98.37	2.59	100.00	100.00	0.00	100.00	100.00	0.00
Subject 5	Sit	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Walk	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Run	94.79	97.65	7.32	100.00	83.20	16.80	96.74	99.00	4.19	98.05	98.69	3.22
Subject 6	Sit	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Walk	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Run	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
Subject 7	Sit	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Walk	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Run	97.35	99.10	3.51	99.56	99.56	0.88	100.00	100.00	0.00	100.00	100.00	0.00
Subject 8	Sit	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Walk	100.00	100.00	0.00	100.00	97.89	2.11	100.00	100.00	0.00	100.00	100.00	0.00
	Run	100.00	100.00	0.00	100.00	99.00	1.00	100.00	100.00	0.00	100.00	100.00	0.00
Subject 9	Sit	100.00	100.00	0.00	100.00	96.45	3.55	100.00	100.00	0.00	100.00	100.00	0.00
	Walk	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00	100.00	100.00	0.00
	Run	89.51	94.47	14.95	99.63	88.08	12.21	95.88	98.46	5.54	98.88	98.14	2.94
Average	Sit	100.00	100.00	0.00	100.00	99.61	0.39	100.00	100.00	0.00	100.00	100.00	0.00
	Walk	100.00	99.93	0.07	100.00	99.77	0.23	100.00	99.87	0.13	99.93	100.00	0.07
	Run	96.17	96.77	6.52	98.76	93.49	7.60	98.06	98.90	2.95	98.72	98.79	2.39

5.4. Summary

This chapter presented the development of the proposed noise-tolerant heartbeat detection method. Two main stages with six steps, including band-pass filter, derivative, squared, Savitzky-Golay moving average, autocorrelation and adaptive threshold have been described. The proposed method has been evaluated using three different data sets and each result of the experiment was discussed in this chapter. The comparison of the proposed method performance with the other algorithms has also been presented. Based on the results, the proposed method performed well despite its use in different noisy conditions. After observing the results, it can be concluded that the proposed method has had a good performance, especially in EM noise. Therefore, the proposed method will be used in the heartbeat classification systems in order to investigate the detection of arrhythmias in a noisy signal as discussed in the next chapter.

Chapter 6
Arrhythmia Detection using Heartbeat Classification Method

6.1. Introduction

The development of heartbeat classification system has been conducted in the previous studies, aiming to improve the performances of detecting arrhythmias [5-7, 30, 41, 70, 73]. However, most of the studies have focused on feature extraction [6-7, 30, 61, 70] and classification method [33-37, 39]. There has been too little attention paid on relating the pre-processing and QRS detection with the heartbeat classification system [8-9]. In addition to that, some previous studies did not consider the noises and artifact from ambulatory environment although they used the ambulatory ECG signal data in their works [6-7, 30, 33-34, 70]. Therefore, in this chapter, the proposed QRS detection was employed to develop heartbeat classification system in order to improve the detection of arrhythmia.

In chapter 5, we have developed the noise-tolerant heartbeat detection method to improve the detection of QRS complex in noisy signal. Thus, in this chapter, the development of a heartbeat classification system for arrhythmia detection using the proposed noise-tolerant heartbeat detection method is presented. The objective pursued in this chapter is to develop and evaluate a heartbeat classification algorithm on ambulatory ECG signal. Four stages consisting of ECG pre-processing, proposed heartbeat detection, feature extraction and classification are described. Since, the ECG-preprocessing and heartbeat segmentation stages has been presented in Chapter 5, this chapter focusing on the feature extraction and classification stages Four classification algorithms will be employed in this study and their performance will be compared to get the best classification model. The performance of the classification model will be validated and presented in the following sections. This study makes a major contribution to the research on arrhythmia heartbeat classification by considering the issues from ambulatory environment and demonstrating the proposed noise-tolerant heartbeat to improve the classification results.

6.2. Heartbeat Classification Method

A methodology for arrhythmia detection using heartbeat classification method in this study referred to a previous work [5]. It was divided into four steps as shown in Figure 6.1: (1) ECG signal preprocessing; (2) heartbeat segmentation; (3) feature extraction; and (4) learning/classification. Since the techniques employed during the preprocessing and heartbeat segmentation directly influenced the final classification results, these first two steps have been focused on and presented previously. However, the combination of the informative features from the feature extraction steps and classification algorithms also played important roles in the heartbeat classification method. Thus, the full heartbeat classification was developed. The components of the method are presented in Figure 6.1. Figure 6.2 shows the block diagram of the heartbeat classification system developed in this study.

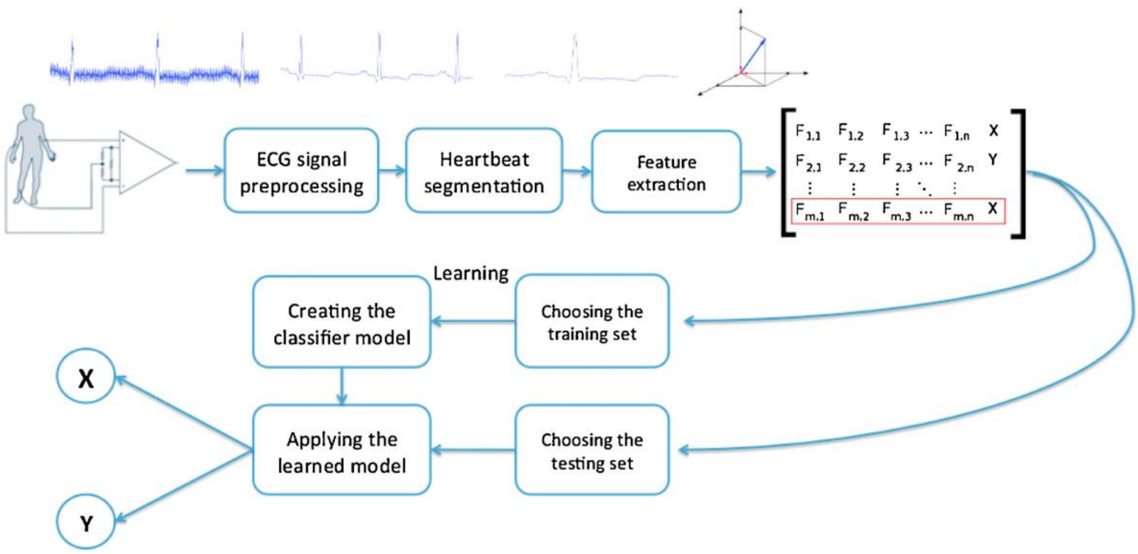


Figure 6.1. A diagram of the heartbeat classification system [5].

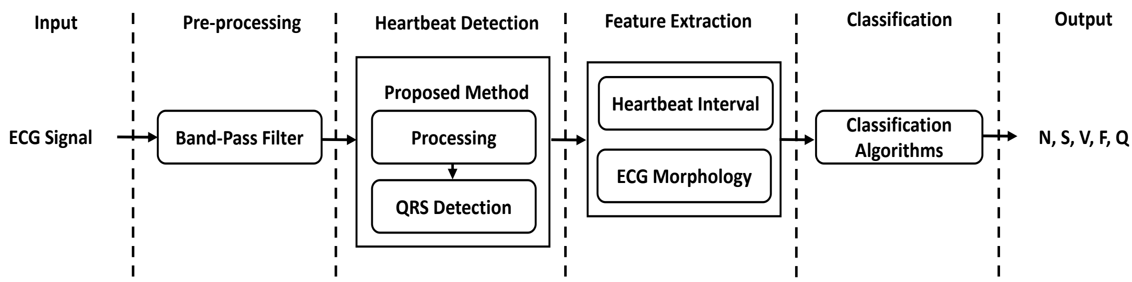


Figure 6.2. The Heartbeat Classification System.

The pre-processing of raw ECG signal was necessary to reduce the noise present in ECG signals in order to improve as much as possible the SNR of the signal. This process can be beneficial to the subsequent fiducial point detection and heartbeat classification because it contributes to the accuracies of the QRS peaks, directly impacting the classification performance. In the heartbeat segmentation step, the fiducial points of ECG signal, which was the QRS complexes were detected. The complete segmentation of ECG usually requires the accurate detection of QRS-peak locations, which can be useful for heartbeat classification, since more information about the heartbeats can be obtained. In this study, pre-processing and proposed heartbeat detection has presented in the Chapter 5. The output from proposed heartbeat detection will be used as the input in the feature extraction stages.

6.2.1. Feature Extraction

The feature extraction step plays an important role to provide reliable results in the classification of heartbeat. Any information extracted from the heartbeat used to discriminate its type may be considered as a feature. The features can be extracted in various forms directly from the ECG signal morphology in the time domain, in the frequency domain or from the cardiac rhythm. The feature extraction phase is concerned with forming feature vectors processed by the classification stage. A feature vector is calculated from each heartbeat for each ECG signal.

As reported in previous studies [5-6,41], the heartbeat interval features also known as the RR interval and the ECG morphology features can be used effectively for arrhythmia classification. The RR interval is the time between the R-peak of a heartbeat with respect to another heartbeat, which could be its predecessor or successor. The RR interval features are computed to characterize the dynamic information of the heartbeat. The variations of this feature are used to reduce the noise interference and are very common; for example, the average of the RR interval in a patient for a certain time interval [5]. With the exception of patients who utilize a pacemaker, the variations perceived in the width of the RR interval are correlated with the variations in the morphology of the curve, frequently provoked by arrhythmias [1]. Thus, the features in the RR interval and ECG morphology have a great capacity to discriminate the types of heartbeats. Figure 6.3 shows the illustration of the RR interval and ECG morphology in an ECG signal.

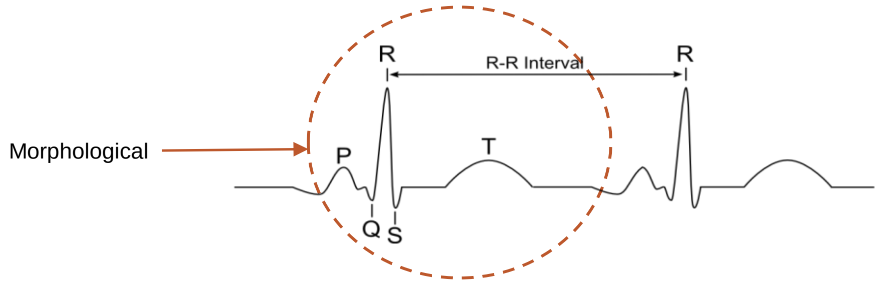


Figure 6.3. The illustration of the RR interval and ECG morphology.

In this study, two groups of features were used based on the heartbeat interval and ECG morphology. The basic idea was to use the dynamic features that were less prone to the noise interference since the focused on this study was for ambulatory signal. Fourteen features were extracted separately to represent each heartbeat, with seven features of heartbeat interval and seven features of ECG morphology described in the next section. Let $R(i)$ be the R-peak position of the i^{th} heartbeat and $RR(i)$ be the current RR interval between $R(i)$ and $R(i-1)$. Table 6.1 lists the features used in this study.

6.2.1.1. Heartbeat Interval Features

The heartbeat interval features were extracted using the information from the R-peak and RR interval. The interval was defined as the interval between two successive R waves. Referring to the previous studies [1-6], seven RR interval features were extracted in this study, including the previous RR interval, the post-RR interval and the variance of three intervals. The previous RR interval (or pre-RR interval) was the RR interval between $R(i)$ and $R(i-1)$. Note that the previous RR interval is the current RR interval. The post-RR interval was the RR interval between the current heartbeat and the following heartbeat, $R(i)$ and $R(i+1)$ (Figure 6.4). The variance of the three intervals was the variance of the RR interval between $RR(i-1),\ RR(i),\ RR(i+1)$.

To acquire the rhythm information of the signal, the local average RR interval, the local standard deviation RR interval, the local root mean square RR interval and the averaged RR interval features were calculated using the Equations 6.1 to 6.4. Local here was identified as the ten intervals surrounding with current heartbeat $R(i)$. The local average RR interval ($RR_{localAVG}$) was determined by averaging the valid RR intervals of the ten RR intervals surrounding a current heartbeat. The local standard deviation ($RR_{localSTD}$) was the standard deviation of the valid RR intervals of the ten RR intervals surrounding a current heartbeat. The local root mean square ($RR_{localRMS}$) was the root mean square of the ten RR intervals surrounding a current heartbeat, and the average RR interval (RR_{AVG}) was the mean of the valid RR interval for a recording.

$$RR_{localAVG} = \frac{1}{10} \sum_{i=-5}^{5} RR(i) \tag{6.1}$$

$$RR_{localSTD} = \sqrt{\frac{1}{9} \sum_{-5}^{5} |RR(i) - RR_{localAVG}|^2} \tag{6.2}$$

$$RR_{localRMS} = \sqrt{\frac{1}{10} \sum_{-5}^{5} |RR(i)|^2} \tag{6.3}$$

$$RR_{AVG} = \frac{1}{N} \sum_{i=1}^{N} RR(i) \tag{6.4}$$

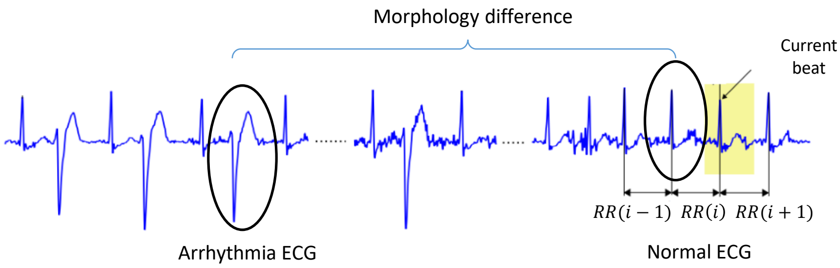


Figure 6.4. Normal and arrhythmia heartbeat interval and morphology features.

6.2.1.2. ECG Morphology Features

One of the most difficult problems in the feature extraction stage is the large variation in the morphologies of ECG waveforms not only from different patients but also within the same patient. To handle this issue, the features from ECG heartbeat were extracted in the time interval of the signal to obtain as much variation of morphology information or normal and arrhythmia beats. The different morphology of normal and arrhythmia beat is shown in Figure 6.4. In this study, the ECG morphology group contained the amplitude values of the ECG signal determined by a window between the R peak and signal time interval. Referring to a previous work [41], seven features were derived in this study: the mean of signal amplitudes between $R(i-1)$and $R(i)$, absolute difference between signal amplitudes at $R(i-1)$and $R(i)$, absolute difference between signal amplitudes at $R(i)$ and $R(i+1)$, mean of signal amplitudes within 0.12-second interval, mean of signal amplitudes within a 0.16-second interval, mean of gradients of signal amplitudes within a 0.12-second interval and mean of gradients of signal amplitudes within a 0.16-second interval.

Table 6.1. List of features used for heartbeat classification.

Group Label	Features
Heartbeat Intervals	Pre RR interval, $RR(i)$
	Post RR interval, $RR(i)$, $RR(i+1)$
	Variance of $RR(i-1), RR(i), RR(i+1)$
	Average RR interval in the ten intervals surrounding a heartbeat
	Standard deviation the ten intervals surrounding a heartbeat

	Root mean square of the ten intervals surrounding a heartbeat
	Average of RR interval in the signal
ECG Morphology	Mean of signal amplitudes between $R(i-1)$ and $R(i)$
	Absolute difference between signal amplitudes at $R(i-1)$ and $R(i)$
	Absolute difference between signal amplitudes at $R(i)$ and $R(i+1)$
	Mean of signal amplitudes within a 0.12-second interval
	Mean of signal amplitudes within a 0.16-second interval
	Mean of gradients of signal amplitudes within a 0.12-second interval
	Mean of gradients of signal amplitudes within a 0.16-second interval

6.2.2. Classification

In the classification stage, the classification algorithms were used for classifying heartbeats into normal and arrhythmias beats. After the feature extraction stage, set of fourteen features were created and using the data, the classification model was constructed. In this study, four types of classification algorithms were adopted with the objective of finding the best model to detect arrhythmia from ECG signals: k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Linear Discriminant (LDA), and Decision Tree (DT). All of the classification algorithms were employed using the Classification Learner toolbox in MATLAB R2018b. Among the classifiers, the k-NN showed better performance in the experiment and it was selected to construct the best learning method with the features from feature extraction phase.

The k-NN algorithm is a supervised classification technique that classifies data points based on the points most similar to it. The k-NN classification algorithm predicts the test sample's category according to the k training samples, which are the nearest neighbors to the test sample, and classifies it to the category that has the largest category probability. Suppose that there are j training categories, as c_1, c_2, ... c_j, and the sum of training samples is N. Also, class X is the same feature vectors as all of the training samples.

When d_i is one of the neighbors in the training set, $y(d_i,c_j)\in\{0,1\}$ indicates whether d_i belongs to class c_j, and $Sim(X,d_i)$ is the similarity function for X and d_i. Then, the probability density function $P(X,c_i)$, for the feature data X, given class c_j, can be written as Equation 6.5 [11].

$$P(X,c_j) = \sum_{di\in kNN} Sim(X,d_i)\cdot y\left(d_i,c_j\right) \tag{6.5}$$

$Sim(X,d_i)$ could be calculated using the Euclidean distance, cosine, and correlation methods. In this study, the Euclidean distance method was selected because it was often used as the distance metric. The k-value was a user-defined constant number of neighbor group elements, and an unlabeled vector was classified by assigning the label that occurred most frequently among the k training samples nearest that query point. In this study, the k-value was initially fixed at 3 [41]. According to the label of the k neighbors and the distributions of the similarity value, the class of the input vector X was discriminated.

6.3. Experimental Setting

In this section, the experimental settings to evaluate the heartbeat classification method is described. The MIT-BIH and AAMI standard was used to evaluate the heartbeat classification. In the MIT-BIH database, there were over 99,092 heartbeats individually labeled as one of 15 possible heartbeat classes and further divided into five main arrhythmia classes, which were N, S, V, F and Q as described in the Table 3.2. In accordance with the standard recommended by the AAMI [78], four records from MIT-BIH which contained paced beats taken from patients fitted with a pacemaker were excluded from this study: record 102, 104, 107 and 217.

The scheme evaluation with the data distribution proposed in a study [6] was adopted as shown in Table 6.2. Using the MIT-BIH dataset, two groups of data were distributed as training (DS1) and testing (DS2) data, each of which contained ECG signals from 22 recordings as shown in Table 6.3. In DS1, the ten-fold cross validation was used for training the classifier to obtain the best learning model. By using this ten-fold cross validation, the entire training DS1 dataset (50,091 beats) was sub-sampled into ten sets, having almost the same distribution of samples from each class. The best learning model with the highest accuracy detection was chosen. Then, the classification model was tested using DS2 with 49,001 beats.

Table 6.2. Data Distribution for Training (DS1) and Testing (DS2) data.

Dataset	MIT-BIH Records [1]
DS1	101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230
DS2	100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234

[1] Each recording is originally discontinuous.

Table 6.3. Summary of heartbeats in Training (DS1) and Testing (DS2) of MIT-BIH.

Dataset	Total beats	N	S	V	F	Q
DS1	50,091	45,432	726	3430	411	92
DS2	49,002	43,745	1777	3055	382	43

To investigate the performance of heartbeat classification on noisy ECG signals, the ECG-noise simulated signal with record 213 was also used as a test dataset. Record 213 was selected because it consisted of a high number of arrhythmia beats and contributed the highest arrhythmia detection in the classification algorithms. Then, the performance of heartbeat classification with the proposed heartbeat detection was compared with the performance of heartbeat classification using the Pan Tompkins algorithm. The confusion matrix [6] was used for the distribution of the multi-class classification problem to evaluate the result attained by a classifier. In this study, the performance was evaluated based on the SE, PP and ACC for both training and testing dataset. The equations of the evaluation metrics are described in Chapter 3.

6.4. Results and Discussion

In this section, the performance results of the heartbeat classification method are presented. Firstly, the performance comparison between the classification algorithms is presented. Based on the comparison of classification algorithm, the best learning model is selected and used for testing. Then, the overall performance of classification method is compared with other previous works to validate the results. The performance of the method in noisy signal is investigated using ECG-noise simulated signal using record 213 at different intensity of MA and EM noise. The performance results and analysis are described in the next section.

6.4.1. Performance of Classification Model

The main focus of the heartbeat classification here was to obtain classification results from machine learning-based classification algorithms in combination with the proposed heartbeat detection to select the best learning classification model. Figure 6.5 provides a performance comparison among different classification algorithms which were k-NN, SVM, LDA and DT using 10-fold cross validation on DS1 for heartbeat classification. Twenty-two records of DS1 as shown in Table 6.2 are used as training datasets. The table shows that k-NN, with k=3, yields the highest accuracy for classification with 98.60% compared with other algorithms. It also achieved higher results for N, S, V, F and Q with the SE being 99.69%, 76.86%, 92.16% 86.62 and 32.81%, respectively while the PP being 99.00%, 92.69%, 97.50%, 87.04% and 65.63%, respectively. After considering the results of classification model in Figure 6.5, the k-NN classification algorithms were selected as the best learning model in this study.

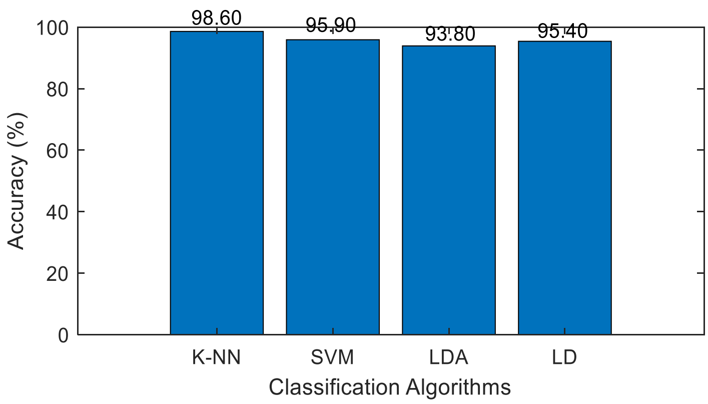


Figure 6.5. Performance comparison of classification models using 10-fold cross validation on DS1 for arrhythmia classification.

6.4.2. Testing of the Classification Model on MIT-BIH

The performance of the k-NN learning model was tested using DS2 dataset. To investigate the performance of the heartbeat classification model, twenty-two records as distribution shown in Table 6.2 were used. Table 6.4 shows the classification performance of the learning model on the heartbeats in DS2. This assessment was unbiased as these beats were not used at any point of the development of the classification model. Note that not all records consisted of all types of N, S, V, F and Q beats (Table 3.2). In general, the performance of the classification model was evaluated when the classifier detected the types of beats consisted highly in the record.

As can be seen in Table 6.4, the classification model performed best on N class compared to other classes since the majority of the samples consisted of normal beats. For the arrhythmia beat, the assessment focused only on supraventricular arrhythmias, S class and ventricular arrhythmia, V class since F and Q class contained the fusion and unknown beats. In addition to that, the arrhythmia beat in V class was the most common arrhythmia correlated with sudden cardiac death as described in Section 1.2.2. Based on the results in Table 6.4, the learning model performed better to detect the arrhythmia beat in V class compared with S class. Even though the performance of detecting V class was much lower compared to N class, the learning model could detect the V class almost in each record that contained ventricular beats.

Figure 6.6 shows the confusion matrix used to test the learning model using the record 213 in DS2. The confusion matrix presented the summary table of beat by beat performance, providing insights into how each class was classified. The rows of the confusion matrix corresponded to the true class and the columns corresponded to the predicted class. Diagonal and off-diagonal cells corresponded to correctly and incorrectly classified observations. A summary of correctly (blue color) and incorrectly (orange color) classified observations for each predicted and true class was shown in percentages. The results showed that 2620 N beats, 166 V beats, 19 S beats and 93 F beats were classified correctly. It also showed that distinguishing normal beats from fusion beats was inherently a difficult problem as fusion beats were a union of ventricular and normal beats.

Table 6.4. Evaluation of classification method on records in DS2.

Record	Number of beats					N		S		V		F		Q	
	N	S	V	F	Q	SE (%)	PP (%)	SE (%)	PP (%)	SE (%)	PP (%)	SE (%)	PP (%)	SE (%)	PP (%)
100	2239	33	1	-	-	100.00	98.80	3.00	100.00	0.00	0.00	-	-	-	-
103	2081	2	-	-	-	100.00	99.90	0.00	0.00	-	-	-	-	-	-
105	2503	-	41	-	23	99.10	99.20	-	-	73.20	46.90	-	-	0.00	0.00
111	2122	-	1	-	-	92.70	100.00	-	-	100.00	0.60	-	-	-	-
113	1787	6	-	-	-	99.90	100.00	100.00	85.70	-	-	-	-	-	-
117	1534	1	-	-	-	98.70	100.00	100.00	100.00	-	-	-	-	-	-
121	1860	1	1	-	-	99.90	99.90	0.00	0.00	100.00	50.00	-	-	-	-
123	1510	-	-	-	-	100.00	100.00	-	-	-	-	-	-	-	-
200	1736	30	819	1	1	98.20	95.10	13.30	4.00	69.60	99.10	100.00	0.80	0.00	0.00
202	1945	42	16	1	-	99.50	98.40	4.80	50.00	100.00	50.00	0.00	0.00	-	-
210	2403	17	130	6	2	96.70	98.00	0.00	0.00	75.40	53.60	0.00	0.00	0.00	0.00
212	2747	-	-	-	-	98.90	100.00	-	-	-	-	-	-	-	-
213	2641	27	207	360	1	99.20	91.20	70.40	76.00	80.20	86.90	25.80	63.30	0.00	0.00
214	1962	-	249	1	3	99.80	93.60	-	-	33.30	94.30	0.00	0.00	0.00	0.00
219	2051	7	52	1	-	99.80	99.40	0.00	0.00	90.40	95.90	0.00	0.00	-	-
221	2022	-	371	-	-	99.40	99.70	-	-	96.20	99.20	-	-	-	-
222	2140	196	-	-	-	95.90	93.20	1.00	50.00	-	-	-	-	-	-
228	1676	3	359	-	11	96.80	97.50	0.00	0.00	88.30	84.80	-	-	9.10	20.00
231	1568	1	2	-	-	99.90	99.90	0.00	0.00	50.00	100.00	-	-	-	-
232	398	1362	-	-	2	98.50	24.40	2.35	97.00	-	-	-	-	0.00	0.00
233	2120	6	806	11		93.80	94.30	50.00	3.00	76.20	94.30	27.30	3.60	-	-
234	2700	43	-	-	-	100.00	98.80	25.60	100.00	-	-	-	-	-	-
					Maximum	100	100	100	100	100	100	100	63.30	9.10	20.00
					Minimum	92.70	24.40	0.00	0.00	33.30	46.90	0.00	0.00	0.00	0.00

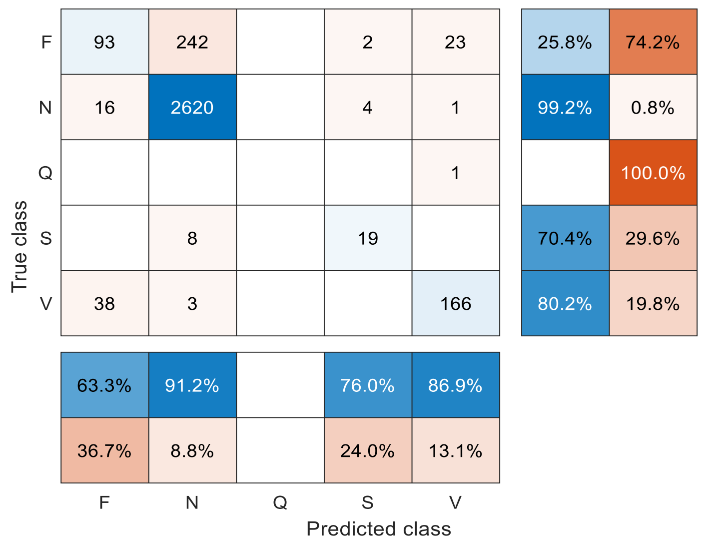
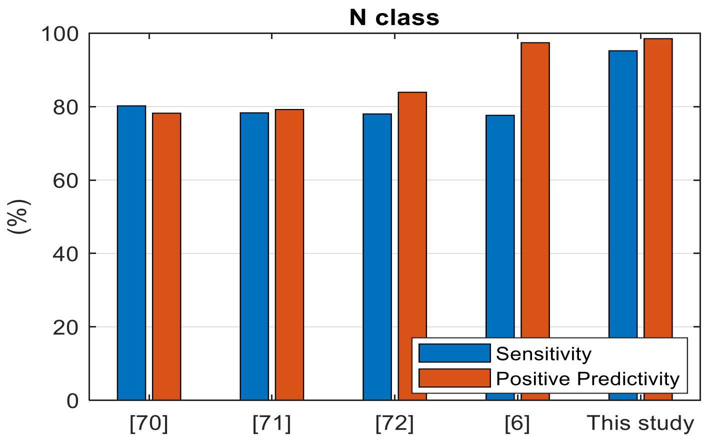


Figure 6.6. The confusion matrix used to test the learning model using the record 213 in DS2.

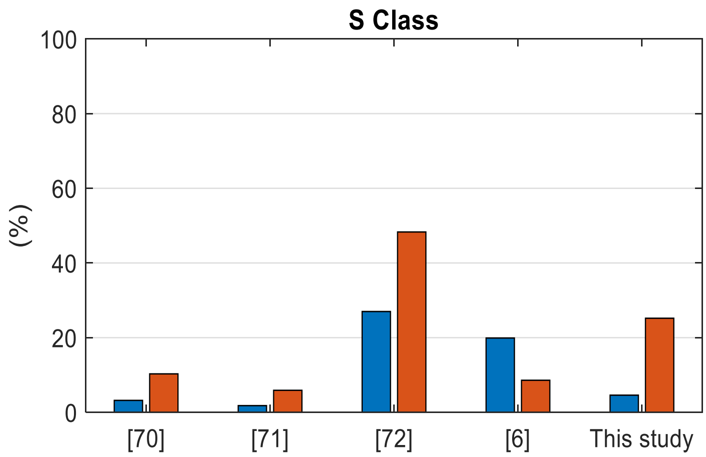
6.4.3. Comparison with other Heartbeat Classification Method

For the comparison, the performance of classification method was tested with all records in DS2 following the distribution data in Table 6.2. A total of 43,745 beats of N class, 1777 beats for of class and 3055 of V class, 382 beats of F class and 43 beats of Q class was used. Only the majority of arrhythmias classes, which were S and V, were evaluated because most problematic arrhythmias were found with this type. Furthermore, most of the previous works in heartbeat classification also focused on these three classes as reported previously [32, 38-39]. As stated in many previous works [5-7], there were issues in the evaluation process for heartbeat classification regarding the biased selection of the datasets used in the training and testing, contributing to highest detection results. Many previous works did not follow the AAMI recommendations by using different records for training and testing set, and it has become difficult to perform the comparison.

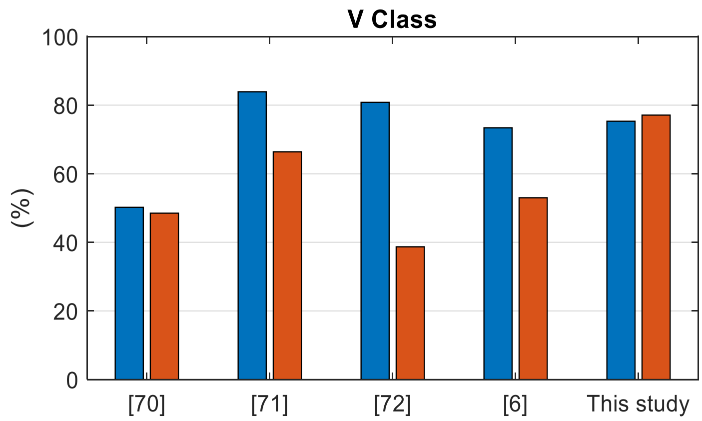
Considering the issues stated, four previous works [6, 32, 38-39] were selected for the comparison. These works were selected because they used the same distribution of testing and training dataset and the same classes of heartbeat categories in the experiments. Figure 6.7 (a), (b), and (c) shows the comparison results of the selected work for N, S and V class. Note that all the works in the previous study have been re-evaluated by using the protocol recommended by AAMI and using the proposed division scheme [6] which has been discussed in previous works [5, 69]. Based on the comparison results, the performance of the work in this study was better than others to classify the N class, with 95.20% of SE and 98.50% of PP. The classification results also showed that the percentage of PP for V class was higher than others with 77.10% even though the SE was much lower from the previous works [42-43]. All of the results of S class were lower in all previous works included in this study. From the analysis, the reason of the low detection of S class was because of insufficient information in the training dataset in which only 726 beats of S class were used compared with the 1777 beats for the testing dataset as shown in Table 6.3. This condition affected the classification performance since the predictive model would perform better if the constructed model had more information to analyze the patterns.



(a)



(b)



(c)

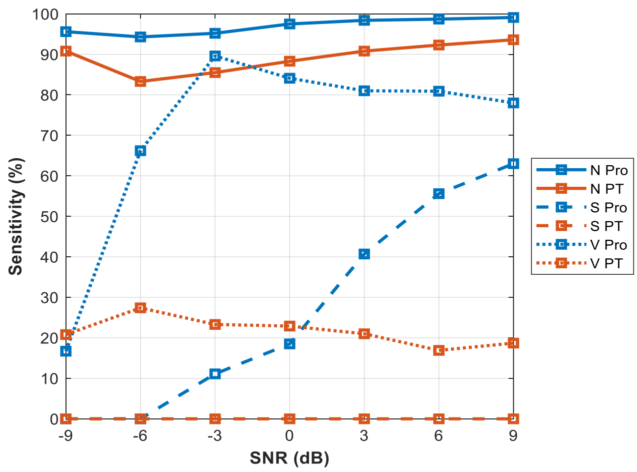
Figure 6.7. Performance comparison of classification results in this study with other previous studies for (a) N class, (b) S class and (c) V class.

6.4.4. Evaluation on Noisy ECG Signal

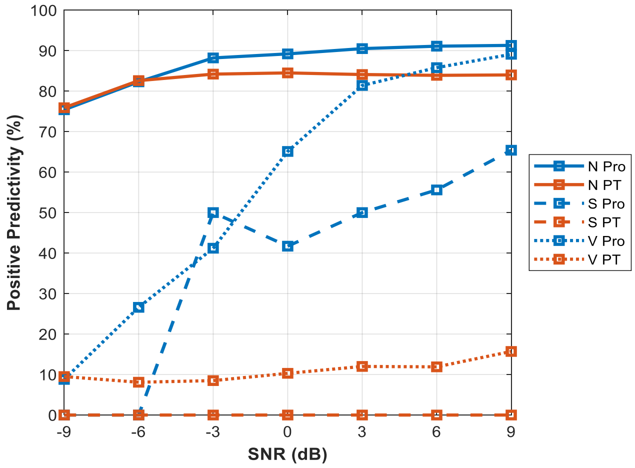
Figure 6.8 (a) and (b) shows the SE and PP performance of heartbeat classification of N, S and V class using the ECG-noise simulated signals from record 213 contaminated with MA at SNR of 9 dB to -9 dB. In the figures, N Pro, S Pro and V Pro is a N, S and V values from proposed method while N PT, S PT and V PT is a values from Pan Tompkins algorithm. In general, the performance of the method decreased with the lower SNR and the best performance was with SNR of 9 dB. Compared with the original signal record 213, where the performance of N class was 99.20% of SE and 91.20 of PP; S class was 70.40% of SE and 76.00% of PP; and V class was 80.20 % of SE and 86.90% of PP as shown in Table 6.4, the performance of simulated signal with SNR of 9 dB was lower since it contained noise higher than the original ones. However, the performance of PP was high compared to the original signal, showing that the method was able to reduce false detections in noisy signal even though the noise affected the performance of SE.

The N class had a good performance with lower simulated signal at SNR of -9, producing 95.60% of SE and 75.40% of PP. For the arrhythmia beat, focusing on V class, the method performed better at SNR of 3 dB to 9 dB with both SE and PP being higher than 78%. The results showed that the method was sensitive when the signal was below SNR of 0 dB, contributing to the higher false detection. Different from V class, the performance on S class was much lower. However, compared with V class that had an increasingly higher false detections, the performance of S class showed that the higher number of misdetections contributed to lower SE. The best performance of S class was when the SNR was above 6 dB at which the percentage of SE and PP was higher than 50%.

To validate the performance of classification method with the proposed heartbeat detection in noisy signal, the experiment using Pan Tompkins algorithm as the heartbeat detection method was performed. The Pan Tompkins was performed using the same features and classification algorithm. Figure 6.8 shows the comparison results of the classification method using the Pan Tompkins algorithm with the proposed method. As shown in the Figure 6.8, the performance of the classification method was high in normal beats. However, the detection of arrhythmias in S and V class was both lower than 20% in the signal contaminated with MA noise. Compared with the Pan Tompkins algorithm, the proposed heartbeat detection in this study performed much better to detect the arrhythmia in noisy signal.



(a)

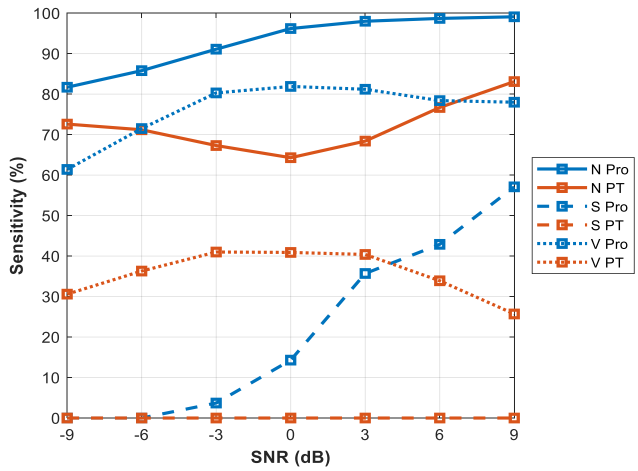


(b)

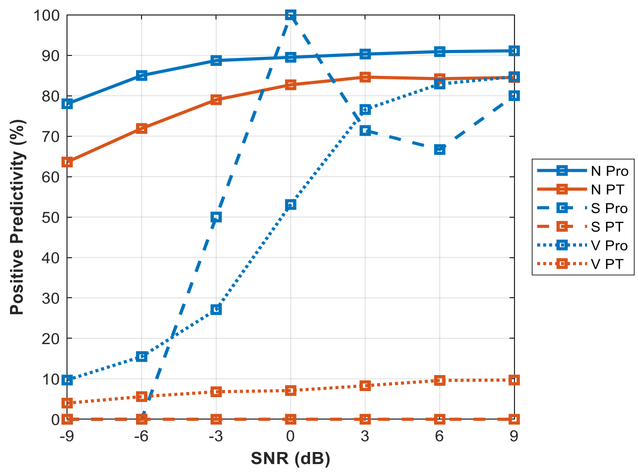
Figure 6.8. Comparison performance of the (a) SE and (b) PP of the proposed heartbeat detection method and Pan Tompkins in classification system with MA noise.

The performance of classification method was evaluated using the simulated signal with motion artifacts. Figure 6.9 (a) and (b) shows the comparison performance of heartbeat classification method and Pan Tompkins algorithm of N, S and V class using the record 213 contaminated with EM at SNR of 9 dB to -9. Based on the results, the proposed method and Pan Tompkins showed lower performance with lowest SNR.

Both of the method showed good performance in detecting N class where the percentage performance with the proposed method being above 81.70% of SE and 78% of PP; and that of Pan Tompkins algorithm was 72.60% of SE and 63% of PP. In the V class, the proposed method showed good performance at SNR of 3 dB to 9 dB with the percentage above 76.60% of PP and 78% of SE. The false detections of V class in the simulated signal below SNR of 3 dB highly increased and contributed to the drop in the percentage of PP. However, it showed better performance than Pan Tompkins that contributed below 9.70% of PP at SNR of 9 dB. Similar to the MA noise, in the EM noise, the performance of classification method also showed higher misdetections in S class. Based on both results, the proposed heartbeat detection with classification algorithm performed better in EM noise.



(a)



(b)

Figure 6.9. Comparison performance of the (a) SE and (b) PP of the proposed heartbeat detection method and Pan Tompkins in classification system with EM artifact.

6.5. Summary

This chapter has presented the development of heartbeat classification system by using the proposed noise-tolerant heartbeat detection method. Four stages consisting of ECG pre-processing, proposed heartbeat detection, feature extraction and classification have been described. After the evaluation of the classification algorithms, the k-NN algorithm was used to construct the classification model and be tested in the experiments. The protocol recommended by AAMI and the data division scheme proposed in a study

[6] were used to solve the evaluation issues in the heartbeat classification problem. Based on the results, the proposed heartbeat classification system performed better to classify normal and ventricular beats, except the supraventricular beats that needed more information for constructing the model. In the noisy ECG signal, the classification method also performed better compared to using pan Tompkins algorithm as a heartbeat detection. It showed that the proposed heartbeat detection as described in Chapter 5 contributed to improving the classification results in the noisy ECG signal.

Chapter 7
Conclusion and Future Work

In this chapter, the main contributions of the thesis are summarized and the works in previous chapters are concluded. Some of the future works as a continuation of the thesis are also suggested.

7.1. Summary

The detection of heartbeat is one of the most important processes that influence the accurate detection of arrhythmias in the ambulatory ECG signal. Therefore, there is a need to develop a robust heartbeat detection method against the high-intensity noise produced during daily-life activities. For that reason, this thesis has taken the initiative to propose the noise-tolerant heartbeat detection method for the arrhythmia classification system. To achieve this goal, these questions need to be clarified. First, what types of noise and artifact are produced in the ambulatory ECG signal during daily life activities? Second, what is the type of noise that affects the performance of detecting a heartbeat the most? Third, does this noise affect the heartbeat morphology of the signal? Fourth, what are the levels of noise intensity that affects the performance detection of a heartbeat? Fifth, how is the performance of heartbeat in a noisy signal that contains arrhythmia beats?

To answer these questions, the first objective of this study was developed. The heartbeat detection method was decided to be employed to be able to understand and interpret the results and issues during the development of the method. The study of characteristics of ambulatory ECG signal recorded during daily life activities showed that among various types of noise, the BW, MA and EM were most troublesome noise. The findings showed that the EM noise had the highest number of misdetections and false detections that contributed to the poorest detection performance, followed by the MA and BW noise. The findings also implied that the signal contaminated with noise and artifacts degraded the ECG morphology of the signal, especially when contaminated with EM noise. The relationship between the types of noise and their different intensity level on beat detection performance showed that the effects of EM and MA noise were higher to the detection process, degrading their performance as reflected in the contents of Chapter 4. In addition to that, the signal with noise has disrupted the arrhythmia beats, affecting the detection performance compared with the clean signal.

Further improvement was required and the second objective was developed in which the heartbeat detection method with noise tolerance was proposed. The autocorrelation techniques that generated a period of heartbeats were used to reduce the misdetections and false detections in fiducial points. Another important method to be robust against the noisy signal was using the smoothing technique by SGMA where it could increase the quality of the noisy signal. As a result, a heartbeat detection method with band-pass filtering, differentiation, squared, SGMA, autocorrelation techniques with the adaptive threshold was developed. With this proposed method, it slightly improved the performance of QRS detection in noisy signal especially with signals contaminated with EM noise. The results showed that the proposed method yielded a good result during activities such as walking and running in real ECG data. The methodology was explained and results were presented in Chapter 5.

To achieve the main goal in this study, the adaptation of the proposed heartbeat detection in the arrhythmia detection system was examined. For this purpose, the heartbeat classification approach for arrhythmia detection was developed as the third objective. Several features were explored to obtain the features that had a physiological meaning, and were simple to compute and robust against the noise present in ECG. At the same time, the methodology to classify the features was discovered. The features based on heartbeat interval and ECG morphology were extracted, and the k-NN algorithm was used to classify the heartbeats. Finally, a heartbeat classification system that adapted the proposed heartbeat detection in Chapter 5 was evaluated and the results were discussed in Chapter 6.

7.2. Conclusion

In this section, the conclusions drawn through the chapters of the thesis are summarized. Starting with emphasizing the importance of the detection of QRS complex to detect the arrhythmias in order to predict the sudden cardiac death in ambulatory monitoring, the process of understanding the problem is needed. Without a proper understanding of the basic problem, it is impossible to design a robust heartbeat detection system against the noisy signal. It is important to perform the experiment to evaluate the effects of a noisy signal on heartbeat detection performance. In the applications of the detection of QRS, there exist variations of noise conditions, proving that false detection of heartbeat misleads the detection performance of all algorithms. It can be concluded that until the artifact in the signals cannot be accurately reduced, the algorithms will not be capable to provide the accurate information required in the detection of arrhythmias.

The proposed heartbeat detection showed a good performance to reduce false detections and misdetections. The importance of identifying the slope of the QRS in the condition affected by various higher amplitude noise has become one of the true challenges. To smooth the signal and generate the length period as a reference to estimate the slope of the QRS have contributed to the good detection performance of the proposed method. In fact, the threshold-based methods are traditional compared with the other algorithms and are sensitive to noise. The performance of the proposed method has proven to be well against the noisy signal. From this study, the importance of accuracy and error detection as a measure to evaluate the overall performance of QRS detection is also shown.

The accuracy of heartbeat detection becomes one of the most important characteristics of a heartbeat classifier. The experiment has shown that it is possible to perform arrhythmia classification in noisy signal data. When applying the classification of heartbeats, there exist large variations of patients with different quality of ECG signal, thus the performance of classification can be misleading. Therefore, it is more important to have a different subjects, than a small number of repeated subject with ECG signal recording to avoid the biased result in the classification performance. This fact reinforces the importance of evaluating a classifier with the standard ECG arrhythmias database especially in noisy ECG signals to have a better estimation of its real performance.

All the comparisons performed in the previous chapters have been performed in a fair manner up to the best of our knowledge. The works included in the comparisons have comparable methodologies and are of the state of the art. To conclude, the results presented in this thesis represent a performance improvement with respect to the published works in the field of heartbeat detection and arrhythmia classification.

7.3. Future Work

During the study performed for this thesis, a number of future avenues for further research has been identified. Below are some of the identified possible future works:

1. *Test the proposed method with the other real signal data.* During this study, it was difficult to find or collect the ECG signal from arrhythmia patients especially during high-intensity activities such as exercising. The real-life signals available did not have annotations of heartbeat or arrhythmia beat as practiced in the MIT-BIH Database. Thus, it is necessary to verify the performance of the proposed method using other real ECG signals from arrhythmias patients in the future.

2. *Improve QRS detection in arrhythmia beats.* In Section 5.3.1, the lower results of the QRS detection was presented because of the dynamic signal due to the arrhythmia beats. It is clear that the proposed method still has limitations in signal with dynamic arrhythmia beats. Therefore, the parameter settings or new techniques should be investigated to improve this part.

3. *Investigate the others noise reduction or artifact removal method to detect the QRS complex.* Application of some other methods such as adaptive filters to reduce the artifact in the ECG signal is of interest for QRS detection. The adaptive filters need the noise reference input from other signals, such as accelerometer or electromyography signal that can measure the motion information of the signal. To use more than one signals may probably lead to reduced noise and improved SNR signal.

4. *Improve the classification model for supraventricular heartbeats.* Throughout Chapters 6, the weakest point of all the classifiers presented was the supraventricular class performance. From Chapter 6, it is clear that the features models and k-NN algorithms still have limitations to discriminate the supraventricular class. New features and classification strategies should be explored to improve this aspect.

5. *Signals such as the blood pressure or the plethysmography signal are of much interest for heartbeat classification.* In this study, only ECG signal was used to develop the classification model. Using any signals that include the mechanical counterpart can allow better characterization of the heart function in an ambulatory monitoring. Therefore, to include other signals in the classification model would probably lead to performance improvement.

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