European Postgraduate Programme on Biomedical Engineering

MASTER THESIS

ECG Event Detection & Recognition using Time-Frequency Analysis

NEOPHYTOS NEOPHYTOU
PATRAS 2012
Διατηρητικό Πρόγραμμα Μεταπτυχιακών Σπουδών στη Βιοϊατρική Τεχνολογία

ΔΙΠΛΩΜΑΤΙΚΗ ΕΡΓΑΣΙΑ

Ανίχνευση και Αναγνώριση συμβάντων ΗΚΓ με ανάλυση Χρόνου-Συχνότητας

ΝΕΟΦΥΤΟΣ ΝΕΟΦΥΤΟΥ
ΠΑΤΡΑ 2012
Τριμελής Εξεταστική Επιτροπή

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I would like to express my sincere gratitude to my supervisor Professor Costas Pitris for his continuous support of my Master's thesis. His knowledge and personal guidance have been the essential keys for the completion of this work. I could never imagine having a better advisor.

I am deeply grateful to the head of the Biomedical Engineering Department, University of Patras, Professor Nicolaos Pallikarakis for giving me the opportunity to study at the European Postgraduate Programme on Biomedical Engineering and for the knowledge I acquired, that has provided a good basis for the present thesis.

I would like to say a big “thank you” to Dr. Emil Valchinov for his eagerness and his important support and directions.

My sincere thanks to Ms Eleni Panoutsopoulou, for her great patience and continuous administrative support, even when I asked for it at the last minute.

Special thanks to my family and to my friends for every kind of support they provided me. Particularly, I would like to express my love to my friends Federica Di Maio, Marica Marrese and Andri Maria-Anastasia who will travel so long to attend the presentation of my thesis.
ABSTRACT

Electrocardiography (ECG) has been established as one of the most useful diagnostic tools in medicine and is critical in the management of various heart conditions. Automated or semi-automated ECG analysis algorithms are expected to play an important role in the utilization of the ECG data. The correct identification of the QRS complexes is a fundamental step in every ECG analysis method. A major problem that is often encountered in automatic QRS detection is the presence of artifacts in the ECG data, which cause considerable alterations to the signal. Some common filters can smooth the effect of the artifacts, however they cannot eliminate them due to their spectral frequency overlap with the signal components.

In this thesis, the objective was to develop a method, based on Time-Frequency Analysis that would be able to automatically detect and remove artifacts in order to increase the reliability of automatic QRS detection. The ECG data used for this purpose was taken from the Physionet library and more specifically from the MIMIC II database. The data in this database was acquired from ICU patients and it contains various types of rhythms as well as artifacts.

First, a Graphical User Interface (GUI) was developed in order to manually annotate ECG data and was used for creating the ground truth for testing the methods developed. The Time-Frequency Analysis method used for the analysis of the ECG data, was based on a time-varying Autoregressive (AR) model whose solutions were obtained using Burg’s method. Several factors that affect the effectiveness of the method were investigated in order to optimize the algorithm experimentally.

any artifact or not. This is performed with a correct classification rate of 95.56%.
The second step was the “Artifact Detection and Removal,” which could detect and remove the artifact area with an accuracy of 95.60% based on each signal sample identified as artifact or not. The final step, the “QRS Complex Detection,” correctly identified 92% of QRS complexes (322 out of 335 annotated QRS complexes).

Finally, the proposed method was compared with one of the most commonly used methods in ECG analysis, the Wavelet Transform Analysis (WTA). The two methods were tested on exactly the same dataset. The WTA resulted in an overall score of 65.3% mainly due to the large number of false positive detections in the regions of artifact.
ΠΕΡΙΛΗΨΗ

Το ηλεκτροκαρδιογράφημα (ΗΚΓ) έχει καθιερωθεί ως ένα από τα πιο χρήσιμα εργαλεία διάγνωσης στην ιατρική και είναι πολύ σημαντικό στη διαχείριση καρδιαγγειακών παθήσεων. Αυτοματοποιημένοι ή ημι-αυτοματοποιημένοι αλγόριθμοι ανάλυσης του ΗΚΓ αναμένεται να έχουν σημαντικό ρόλο στη χρήση των δεδομένων του ΗΚΓ. Η σωστή αναγνώριση των συμπλεγμάτων Ερίληψης του ΗΚΓ αναμένεται να είναι ένα από τα πιο χρήσιμα εργαλεία διάγνωσης στην ιατρική και είναι πολύ σημαντικό στη διαχείριση καρδιαγγειακών παθήσεων.

Αυτοματοποιημένοι ή ημι-αυτοματοποιημένοι αλγόριθμοι ανάλυσης του ΗΚΓ αναμένεται να έχουν σημαντικό ρόλο στη χρήση των δεδομένων του ΗΚΓ. Η σωστή αναγνώριση των συμπλεγμάτων Ερίληψης του ΗΚΓ αναμένεται να είναι ένα από τα πιο χρήσιμα εργαλεία διάγνωσης στην ιατρική και είναι πολύ σημαντικό στη διαχείριση καρδιαγγειακών παθήσεων. Αυτοματοποιημένοι ή ημι-αυτοματοποιημένοι αλγόριθμοι ανάλυσης του ΗΚΓ αναμένεται να έχουν σημαντικό ρόλο στη χρήση των δεδομένων του ΗΚΓ.

Η σωστή αναγνώριση των συμπλεγμάτων Ερίληψης του ΗΚΓ αναμένεται να είναι ένα από τα πιο χρήσιμα εργαλεία διάγνωσης στην ιατρική και είναι πολύ σημαντικό στη διαχείριση καρδιαγγειακών παθήσεων. Αυτοματοποιημένοι ή ημι-αυτοματοποιημένοι αλγόριθμοι ανάλυσης του ΗΚΓ αναμένεται να έχουν σημαντικό ρόλο στη χρήση των δεδομένων του ΗΚΓ. Η σωστή αναγνώριση των συμπλεγμάτων Ερίληψης του ΗΚΓ αναμένεται να είναι ένα από τα πιο χρήσιμα εργαλεία διάγνωσης στην ιατρική και είναι πολύ σημαντικό στη διαχείριση καρδιαγγειακών παθήσεων.

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Στην παρούσα εργασία στόχος ήταν η ανάπτυξη μιας μεθόδου, βασισμένης στην Ανάλυση Χρόνου-Συχνότητας, που θα είναι σε θέση να εντοπίσει αυτόματα και να αφαιρέτικα τεχνητά σφάλματα σημάτων, ώστε να έχουμε μια πιο αξιόπιστη μέθοδο αυτόματης ανίχνευσης των Ερίληψης. Τα δεδομένα ΗΚΓ που χρησιμοποιήθηκαν για το σκοπό αυτό λήφθηκαν από τη βιβλιοθήκη Physionet και πιο συγκεκριμένα από τη βάση δεδομένων MIMIC II. Τα δεδομένα σε αυτή τη βάση δεδομένων προέρχονται από ασθενείς της Μονάδας Εντατικής Θεραπείας, και ως εκ τούτου, περιέχουν διάφορες είδη ρυθμών αλλά και τεχνητών σφαλμάτων.

Αρχικά, ένα Γραφικό Περιβάλλον Χρήστη (GUI), σχεδιάστηκε για τη χειροκίνητη σηματοδότηση των διάφορων περιοχών ΗΚΓ σημάτων και χρησιμοποιήθηκε για τη δημιουργία των αληθινών αποτελεσμάτων για δοκιμή της μεθόδου. Η Ανάλυση Χρόνου-Συχνότητας έγινε με τη χρήση ενός χρονικά μεταβαλλόμενου Αυτοπαλινδρομικού (AR) μοντέλου οι λύσεις του οποίου βρέθηκαν με τη μέθοδο Burg. Ακολούθησε η διερεύνηση διαφόρων παραγόντων που επηρεάζουν την αποτελεσματικότητα της μεθόδου, προκειμένου να βελτιστοποιηθεί ο αποτελεσματικός της μεθόδου.
πειραματικά η μέθοδος.

Ο αλγόριθμος που υλοποιήθηκε εκτελεί τρεις βασικές λειτουργίες: “Artifact Hypothesis Testing,” “Artifact Detection and Removal” και “QRS Complex Detection.” Κατ’ αρχήν, το βήμα “Artifact Hypothesis Testing” εξετάζει αν το σήμα περιέχει τεχνητό σφάλμα ή όχι, με το ποσοστό σωστής ταξινόμησης να ανέρχεται στο 95.56%. Το δεύτερο βήμα, η ανίχνευση και αφαίρεση της περιοχής του τεχνητού σφάλματος, έγινε με ακρίβεια 95.60% με βάση το πόσα σημεία του σήματος αναγνωρίστηκαν ως τεχνητό σφάλμα ή όχι. Τέλος, το συνολικό ποσοστό ορθής ανίχνευσης των συμπλεγμάτων QRS ήταν 92% (322 από τα 335 QRS που επισημάνθηκαν χειροκίνητα).

Τέλος, έγινε μια σύγκριση μεταξύ της προτεινόμενης μεθόδου και μιας μεθόδου ανάλυσης ΗΚΓ που χρησιμοποιείται πολύ συχνά, της ανάλυσης με Μετασχηματισμό Wavelet (WTA). Οι δύο μέθοδοι δοκιμάστηκαν στα ίδια ακριβώς δεδομένα. Η ορθή ανίχνευση των συμπλεγμάτων QRS με τη μέθοδο WTA ήταν 65.3% κυρίως λόγω του μεγάλου αριθμού ψευδώς θετικών αποτελεσμάτων στις περιοχές των τεχνητών σφαλμάτων.
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CHAPTER 1
INTRODUCTION

1.1 Electrocardiography

Introduction
The heart is one of the most critical organs in the human body, thus the development of methods for monitoring its functionality is crucial. Electrocardiography is considered to be one of the most powerful diagnostic tools in medicine that is routinely used for the assessment of the functionality of the heart. The Electrocardiogram (ECG) is the conventional method for non-invasive interpretation of the electrical activity of the heart in real-time. The electrical cardiac signals are recorded by an external device, by attaching electrodes to the outer surface of the skin of the patient’s thorax. These currents stimulate the cardiac muscle and cause the contractions and relaxations of the heart [1]. The electrical signals travel through the electrodes to the ECG device, which records them as characteristic waves. Different waves reflect the activity of different areas of the heart which generate the respective flowing electrical currents. Figure 1 shows a schematic representation of a normal ECG and its various waves.

 Characteristics of normal Electrocardiogram

A normal ECG consists of a P wave, a QRS complex, and a T wave. The P wave is caused by electric currents produced by the depolarization of the atria before their contraction, while the QRS complex is caused by electric currents produced by the depolarization of the ventricles prior to their contraction, during the extending of the depolarization in the ventricular myocardium. The QRS complex usually consists of three different waves, the Q, R, and S waves. Note that both the P-wave, and the waves that form the QRS complex, are depolarization waves. The T wave is caused by the electric currents produced during recovery of the ventricles from the state of depolarization. This process is takes place in the
ventricular myocardium 0.25s to 0.35s after the depolarization. The T wave is characterized as the wave of repolarization. The Figure 1 shows a representation of an ECG with the waves and complexes annotated.

![ECG waves](image)

*Figure 1: Normal ECG with the waves that is consisted noted. [2]*

**Why is the ECG important?**
The ECG has been established as the most common, easiest, way for accurate and rapid diagnosis and management of numerous cardiovascular incidents. A significant number of patients treated in the emergency room (ER) and in the intensive care unit (ICU), present with cardiovascular complaints. In those cases, the need of early, accurate diagnosis as well as rapid, appropriate therapy, reinforce the importance of electrocardiography. Some examples of incidents that are ideally managed with an ECG are chest pain (presenting ST-segment elevation), acute myocardial infarction, acute coronary syndrome, arrhythmias, and even suspected pulmonary embolism [3].

1.2 **Principal Methods for ECG analysis**

*Introduction*
Since digital electrocardiography has been established as the fundamental way for ECG data acquisition, algorithms for automatic ECG analysis, and more specifically automatic QRS complex detection have been the focus of intense research activity [4]. The QRS complex is perhaps the most significant waveform within the ECG and thus its detection is the crucial first step in every automated algorithm for ECG analysis. Due to their characteristic shape, the QRS complexes
serve as the reference point for the automated heart rate determination [5]. After detection, analysis and feature extraction, provide useful information about the current state of the heart. Software QRS detection has been a research topic for more than thirty years. Within the last decade, numerous new approaches have been proposed and compared, in order to find the optimum automatic QRS detection method [6].

QRS Detection-Brief review

Algorithms, which have been developed for the purpose of QRS detection and analysis, have been derived from Artificial Neural Networks [7,8,9,10], genetic algorithms [6], wavelet transforms, and filter banks. Neural Networks have been used for QRS detection, by training adaptive, non-linear ECG signal predictors [6]. In another method, an estimate of the ECG samples was derived by a number of adaptive filters. That estimate was given as a weighted summation of previous samples, with the weights adapting according to the statistics of the signal [8]. Other approaches included signal derivatives, for detection of the steep slope of the QRS complex [4,11,12,13,14,15], cross-correlation methods, where an initial template was aligned to the current ECG signal [8,9], and syntactic approaches, where the ECG signal was represented as a piecewise linear approximation and was analyzed using syntactic rules [4]. Almost all of the proposed algorithms so far, share a common algorithmic structure, that is, a preprocessing stage, including filtering, a feature extraction stage, and a decision stage in which peak detection and decision logic are included [6,16,17,18].

One well-known method that follows the above stages is the Pan-Tompkins Algorithm (PT) [7]. PT is an algorithm, which comprises a bandpass filter to cut off the high, low, and DC noise, a differentiator and a squaring operator that emphasize the steep prominent features, and an adjustable moving window integrator for smoothing. It then uses a filter threshold method for QRS complex detection. The PT algorithm is very good at detecting normal QRS complexes but it has rather poor performance when it comes to detecting abnormal (e.g. wider) QRS complexes.
The wavelet transform method is currently considered to be a state-of-the-art method for automatic ECG analysis and QRS detection. The wavelet transform (WT) is a decomposition of a signal $f(t)$ into a set of basic functions. This transform gives a time-scale representation similar to the time-frequency representation of the Short-Time Fourier Transform (STFT). The WT uses a number of analyzing functions to cause dilations and translations relative to the mother wavelet. Dilations are characterized by the parameter $a$ and translations by a parameter $b$. Examining the components of analyzing functions of varying widths (i.e. dilation parameter $a$) provides information regarding the frequency components of the signal while the translation reflects their variation as a function of time, which is $b$ in the transformed space. By using scaled values for parameters $a$ and $b$, a sequence of functions is obtained, which are called "scales". Low scales give information about high frequency features of the signal since they can react with steep changes, while high scales give information about low frequency signal components [4,6,19,20,21,22,23].

1.3 Artifacts in the ECG

Unfortunately the acquired ECG does not only consist of the components derived from the electrical functionality of the heart, but it is very often contaminated by artifacts that can interfere or interrupt the signal and result in a loss of information. Sometimes, these artifacts might even present with similar morphology as the ECG [34]. The most commonly found artifacts in the ECG are:

1. Power line interference, which is characterized by a frequency of 50 or 60 Hz depending on the country.
2. Steep voltage changes form the loss of contact between the electrodes and the skin that might also saturate. Additionally, the movement of the electrode because of the patients’ motion leads to changes of the impedance between the skin and the electrode and the result is to get some rapid baseline jumps that might saturate as well.
3. Electrical activity from muscle contractions that varies from dc to 10kHz.
4. Baseline drift which is usually caused from respiration at very low frequencies, around 0.1-0.3 Hz [34].

The present of artifacts in the ECG signal significantly hinders its analysis. This occurs because there is a considerable spectral frequency overlap between the artifacts and the signal. Not much work has been done on artifact detection and removal and thus the literature found on this subject is rather limited. Bala Gopakumaran et al. [24] surveyed the ECG artifacts recorded using commercial monitors sold by the four major patient monitor manufacturers (GE Medical Systems, Milwaukee, WI; Phillips Medical Systems, Andover, MA; Datex Ohmeda, Helsinki, Finland; and Ivy Biomedical Systems, Bradford, CT). They also suggest procedures to minimize artifacts during surgery. Although in general those methods can minimize the appearance of artifacts, they are not successful on artifact removal or elimination.

1.4 Time-Frequency Analysis

What is Time-Frequency Analysis?

Traditional methods of signal processing in general, and biomedical signal processing in particular, tend to assume stationary signals [25]. However, most of the biological processes are, in general, characterized as non-stationary, that is, they dynamically change over time [26]. In such cases, analyzing the signal in the time or frequency domain separately might not be so comprehensive [25]. Although time domain gives information about amplitude, it is vulnerable to noise and it provides no information about the frequency spectrum of the signals. On the other hand, the frequency domain offers much information about the spectral content of the signal but lacks most of the information on how the signal changes with time [25,27]. Hence, a method that combines these two could lead to a combination of the advantages of each individual method.

Time-Frequency Analysis (TFA) effectively provides a description of the spectral content as a function of time [25]. Time-Frequency Representations (TFRs) are
two-dimensional (2D) functions, which describe, at the same time, the signal temporally and spectrally. The TFRs show the distribution of the signal’s spectrum over the Time-Frequency plane and contains both the time variations and frequency bands which define the signal [27].

A very widely used tool for TFR is the spectrogram, which uses the Short-Time Fourier Transform (STFT). Some other methods that can be used to generate TFRs are, the Fourier Transform [28], Wavelet Transform [26,27], Cohen class of distributions [26,27], and the recursive autoregressive estimation [26]. In the current work the last method has been used and it will be explained in detail in section 2.4.1. Figure 2 shows an ECG in Time-Amplitude, and the same example in Time-Frequency.

![Figure 2 Normal ECG signal at the top. The second figure is the Time-Frequency Representation (TFR) of the signal of the first. Yellow indicates high signal power while blue indicates low power. Frequencies vary from 0 to ~60HZ, and for a time period of 5 seconds.](image)

**TFA use in ECG analysis**

As it has already mentioned, TFA is widely used for analysis of multi-component non-stationary signals. ECG signals are considered to be as such signals. In this section prior work on ECG analysis using TFA, is going to be briefly reviewed.

Christov et al. [29] examined the capabilities of two TFA-based methods for heart beat classification. The Matching Pursuits (MPs) method for extraction of time-
frequency beat descriptors and QRS pattern recognition method for computation of a large collection of morphological QRS descriptors. TFA using MPs is a better option when the waveforms are repeating (normal beats, blocks, paced beats), while the wide variety of bizarre premature ventricular contractions can be better recognized by morphological analysis. Nair [30] combined two well-accepted methods, the Pan-Tompkins and Wavelet Transform or STFT for time-frequency representation, in order to extract the features of ECG beats. The results give an accuracy of 97.8%. Similar work has been done by Mahmoodabadi et. al [31], made use of TFA using Daubechies wavelets to extract all features of ECG.

1.5 Purpose and Motivation

The purpose of this thesis was to analyze the ECG and more specifically, to find a reliable method for the detection of the QRS complexes. To avoid erroneous results, QRS identification should be preceded by artifact detection and removal from the ECG signal, so that the QRS detection would be more reliable.

The ECG data used for this work was found in the PhysioNet library (www.physionet.org) in the MIMIC II database. MIMIC II database's recordings are taken from ICU patients and, since it is a real-life database, it contains lots of artifacts, which interfere with the normal and abnormal ECG signals.

The method selected for successful artifact detection and removal and then QRS complex detection, was time-frequency analysis using a time-varying Autoregressive (AR) model based on Burg's algorithm. Burg's algorithm is a method for computing the solution of a parametric spectral estimation using an AR model of order p. We named the Time-Frequency representation (TFR) Burg's Spectrogram, inspired from the TFR using a STFT, which is called Spectrogram. Burg’s algorithm (parametric) was selected instead of STFT (non-parametric) for its better frequency resolution, faster convergence for small signals, and flexibility of choosing different AR model orders [32]. Moreover, the
Burg's Spectrogram can be treated as 2D image where one can apply image processing and statistical techniques for analysis and extraction of the desired features. By choosing certain frequency bands of the spectrogram the analysis can be focused on specific components of the signal, e.g. the artifacts, which can be found mostly in high frequency areas. In addition, low frequency and DC noise can be avoided without filtering.
CHAPTER 2
DATA AND METHODS

2.1 ECG Data

Introduction
The ECG data used for the development and testing of the algorithm was taken from the Physionet library, and more specifically from the MIMIC II database. PhysioNet is an online forum for distribution and exchange of recorded biomedical signals and open-source analysis software, also providing facilities for cooperative analysis of data and evaluation of proposed new algorithms. PhysioBank is a large and growing archive of well-characterized digital recordings of biomedical signals for use by the biomedical researchers [33]. It is freely accessible online through the World Wide Web (http://www.physionet.org/).

Multiparameter Intelligent Monitoring in Intensive Care -MIMIC II
The MIMIC II database consists of over 25 thousands intensive care unit (ICU) patient recordings of physiologic signals and vital signs, captured in real-time from patient monitors, and comprehensive clinical data obtained from hospital medical information systems. The MIMIC II Clinical Database contains clinical data from bedside workstations as well as hospital archives. The MIMIC II Waveform Database includes records of continuous high-resolution physiologic waveforms and minute-by-minute numeric time series of physiologic measurements. The ECG waveforms used for this thesis were taken from the MIMIC II Waveform Database. The waveforms sampled at 125Hz and they typically last over 20 hours each [34].
2.1.1 Data categories

Various types of ECG data have been used in this thesis. They can be distinguished into three main categories: Normal Beats, Abnormal Beats, and Artifacts. However, there are some signals, which consist of components from all of the three categories. Examples of the three categories are listed and explained below.

Normal

Normal ECG signals were considered the signals that exhibited normal and identical P, QRS, and T waves without any observable abnormalities or questionable features and without any preprocessing (i.e. filtering). Examples of waveforms considered Normal are shown below. The waveform in Figure 3 can be considered as normal since its particular waves are normal and distinguishable. The high frequency noise present in the signal is not causing significant distortion and it is, therefore, not considered an artifact. Time-Frequency Analysis is sufficiently robust to this type of noise.

![Figure 3 Normal ECG waveform taken from the MIMIC II database.](image)

The signal in Figure 4 represents another type of waveform that has been categorized as Normal. This waveform is moving on a baseline drift. Such signals are considered as Normal since the normal beats are still clearly distinguishable. In addition, Time-Frequency methods are considerably robust to this type of artifact as well.
Abnormal

Abnormal signals are those that contain some abnormal events, e.g. a cardiac arrhythmia, paced beats and premature ventricular contraction. Some examples of abnormal ECGs are shown below.

The waveform in Figure 5 contains abnormal beats. Even though the MIMIC II database does not provide any annotations about the waveforms, (whether they are normal or abnormal and what type of abnormality) the beats in this waveform are clearly abnormal (abnormal QRS complexes, long duration, higher amplitude, and high occurrence rate.)

Artifacts

As it has already mentioned, the waveforms collected in the MIMIC II database are representative of those can be found in ICU. Thus they contain artifacts caused of patient's movements, sensor degradation, transmission errors,
electromagnetic interference and human error. Some artifact-containing ECG waveforms are illustrated below.

In the Figure 6, the end-points of a short duration artifact are indicated by the two green lines. Another example is the high frequency artifact, interfering with the normal ECG of Figure 7, after the 3rd second. Figure 8 shows a missing data artifact, which can be partially overcome using interpolation. Interpolation will be explained in the methods analysis part (2.4.5 Other Methods).

![Figure 6Artifact between the 3rd and 3,5th second. The green lines indicate the start and end point of the artifact area.](image)

![Figure 7Artifact probably because of muscle contractions.](image)

![Figure 8Missing data artifact. The data retrieved by interpolation.](image)
2.2 Data Annotation Graphical User Interface (GUI)

Accurate annotation of the data used in this thesis, was a critical part of the work. In order to evaluate the accuracy of the ECG event-detection algorithm, it was necessary to compare the automatically generated results of the developed algorithm with the actual or desired results and that requires accurately annotated data. A Graphical User Interface (GUI) was developed to facilitate and expedite manual marking of specific points or regions in an ECG waveform and thus to create an annotation database for each waveform. The GUI was created using the MATLAB software.

GUI Description
The GUI was developed using the MATLAB software. The initial working surface is shown in Figure 9. On the top of the GUI figure there are three toolboxes. The first toolbox, located at the top-left corner and labeled “1. Select a Database”, serves for selecting the database of interest. There are two options: either the MIMIC II database or the MIT/BIH Arrhythmia database. If the first option is selected, then there is a pop-up menu that contains a list of patient indication numbers. A patient’s ID is chosen from the list, in order to load and plot a part of its ECG data in the next step. It has to be noted that the patients were chosen randomly among a very large number of patients (over 25 thousands).
Choosing the MIMIC II database

The first choice of databases is the MIMIC II Database. If that is selected, then one patient from the pop-up menu list has to be selected as well (Figure 10).

Choosing the MIT/BIH Arrhythmia Database

Another option is to choose the MIT/BIH Arrhythmia Database. This database was included in the GUI for the purposes of future work which will be dealing
with the recognition of the type of abnormal beats, since they are annotated by specialists in this database. The pop-up menu here gives the option of three kinds of abnormal signals:

i.  *Premature Ventricular Contraction*

ii.  *Paced Beats*

iii.  *Fusion of paced and normal beats*

When one of them selected the algorithm runs over the database’s annotations to find a piece of waveform that contains such an abnormal beat.

The second toolbox, labeled “2. Plotting Toolbox,” includes the plotting preferences, such as the time to begin and the duration of the waveform (reference point is the time that the ECG recording started). After appropriately setting those preferences, the ECG is displayed in the figure window, by pushing the “Plot” button. Additionally there are two buttons “<<Previous” and “Next>>”, for sliding the plotting window to the previews or next number of seconds (according to the set duration), respectively.

![ECG Manual Annotations](image)

*Figure 11 ECG plotted from the MIMIC II database, patient a40392, Begin-Time: 00:00:00 and 5 seconds duration.*

The next step is the marking procedure. The Toolbox labeled “3. Annotating Toolbox” enables the user to manually mark the points and areas of interest and finally save their coordinates in a database. An example is shown in Figure 12.
First, the user must select the radio button of the specific wave or area, and then push the button “Mark”. A cross appears as the mouse pointer. When the user right-clicks somewhere on the plot, an annotation appears at that point (red, green, blue or yellow), and its coordinates are stored in memory. The “Clear” pushbutton erases the coordinates and clears the graph from annotations. The “Save” pushbutton saves each annotated signal into a database.

A very helpful tool, when searching a signal for particular features, is the automatic graph sliding that can be found at the bottom of the GUI figure. Pressing the “Start/Stop” pushbutton enables the user to observe consecutive parts of the waveform. When a part of interest passes through, pressing the same button “freezes” the waveform at that point.

The “Process” button loads another GUI that has been designed for signal processing purposes and it is described in the following section.
2.3 Time-Frequency Analysis Graphical User Interface (GUI)

A Graphical User Interface (GUI) has been developed for assisting in the algorithm development, as well as for easier visualization of the effects of appropriate parameter selection. This GUI allows the user to experiment with individual portions of signals and better understand how the algorithm and the methods work and how they are affected by the various parameters.

GUI Description

The initial GUI window is shown in Figure 13. Using the toolbox “1.Select and Load Signal File,” the user can browse and load a certain signal file that has already been annotated and stored. When the “Browse” button is pressed a dialogue appears that enables the user to choose between four categories of signals: Normal, Artifact, ECG events, and Mixed. The user can then select a Patient Directory and a Signal from the pop-up menus. The “Load” pushbutton will load the selected data and plot it as shown in Figure 14.

![Figure 13 Initial window of the Process GUI](image)
Below the ECG signal the Artifact Hypothesis decision is displayed in red-colored letters. In this case depicted in Figure 16, the signal contains artifact so the Artifact Hypothesis resulted in “YES.” Manual annotations are loaded and displayed on the graph when the checkbox “Show Manual Annotations” (to the left of the Artifact Hypothesis) is selected.

The second toolbox “2. Spectrogram” allows the user to vary the parameters of Burg’s algorithm and thus to decide, after appropriate experimentation, which provide the best results. Also, the spectrogram image is displayed providing the user with a visual way of deciding the frequency ranges of the image to reject or to keep for further processing. Selecting a Burg Window of 15, with overlap of 10, an AR order of 2 and an FFT size of $2^{10}$ results in the spectrogram of Figure 15.
The next step is to either go to toolbox “3. Process Spectrogram” for artifact detection, or to skip step 3 and go directly to step “4. QRS Detection” in the case of the artifact-free signals.

The “3. Process Spectrogram” toolbox, enables the user to choose statistics window and the spectrogram’s frequency band of interest. The “Calcul. Stat.” pushbutton calculates the local neighborhood statistics (STD, Variance and Mean) of the spectrogram, which can be viewed by selecting them from the panel. They are also automatically converted in binary images, using an automatic threshold, and displayed as the last image. “ImClose” and “ImOpen” perform morphological close and open operations on the binary images for removing small objects. The “Edges” pushbutton finds the end-points of the area detected in the binary image and the “Unprocessed BW” button reloads the initial binary image before any processing.

Figure 16 shows an example where the statistics window size was 15x15 and the frequency band selected between 55 and 60Hz. The middle image is the mean and the last image is its binary version. At the bottom of the GUI figure, the button **Show Results** compares the detected area with the annotated area. In
this case the correctly classified area (the sum of the True Positive and True Negative portions of the signal) is 95.93%.

The last toolbox “4.QRS Detection” is used in the case of artifact-free signals. In Figure 17, the frequency band of interest was chosen between 5 and 20Hz. The “Detect R” button performs the summation of the values at each time for the selected frequency range. The resulting 1D data is displayed as the red line, illustrating that the peaks approximately coincide with the R peaks of the ECG signal (blue line).
2.4 Methodology

Introduction

In this section, the various methods that have been used in this thesis, including signal and image processing techniques as well as statistical methods, will be briefly introduced.

2.4.1 Time-Frequency Analysis – Burg’s Method

Time-Frequency analysis (TFA) is a signal processing technique that combines the frequency and time domains to estimate and present time variable spectral information. Hence, it provides a description of the changes of the spectral content as a function of time. The Time-Frequency transform maps the data in the so-called time-frequency plane (t-f plane). A Time-frequency Representation (TFR) for a signal $x(t)$ is given by:

$$ TF_{x}(t, \omega) = \int_{-\infty}^{\infty} x(t)\Phi_{t,\omega}(t)dt $$

(1)
Where, \( \Phi_{T,0}^* \) represents the complex conjugate of the basis function and it varies according to the analysis approach.

**Spectral Analysis**

Spectral Analysis aims to describe the distribution of the power contained in a signal over frequency. That is also called Power Spectral Density (PSD), which is the Fourier Transform of the autocorrelation function of a stationary (i.e. stochastic) signal. The spectral estimation methods are separated into two main categories, parametric and non-parametric methods.

**Parametric Vs. Non-parametric**

The non-parametric methods are those which extract the PSD directly from the signal itself, in contrast with the parametric methods, which first estimate some parameters (coefficients) of the linear system that hypothetically generates the signal, and then estimate the PSD. It is assumed that the signal is the output of a linear system driven by white noise. The most commonly used linear system model is the all-pole model. It is a filter that has all its zeros at the origin of the z-plane. If the input in such a filter is white noise, then the output is an Autoregressive (AR) process often referred to as an AR method of spectral estimation. The AR methods can better describe data which have large PSDs at certain frequencies. Parametric methods tend to provide superior results than the classical non-parametric when the data of the available signal is relatively short. Moreover they give smoother estimates of the PSD as well as higher resolutions compared to non-parametric methods.

All AR methods derive a PSD estimate that is given by:

\[
\hat{P}(f) = \frac{1}{F_s} \cdot \frac{p}{1 - \sum_{k=1}^{p} \alpha_p(k) e^{-\frac{i2\pi kf}{F_s}}}^2
\]  

\( (2) \)
**Burg’s Method**

Burg's method was chosen for spectral estimation of the ECG data and for deriving the time-frequency features of the signals. Burg’s method is an AR spectral estimation method that minimizes the forward and backward prediction errors by constraining the AR parameters to satisfy the Levinson-Durbin recursion [35]. Levinson-Durbin recursion is an algorithm for linear prediction of an all-pole IIR filter with deterministic autocorrelation sequence. Hence, it computes the AR parameters, \( A(z) \):

\[
H(z) = \frac{1}{A(z)} = \frac{1}{1 + a(2)z^{-1} + \cdots + a(n+1)z^{-n}}
\]  

(3)

where, \( A(z) \) is the polynomial of order \( n \), that is \( a=[1, a(2), \ldots, a(n+1)] \), the filter coefficients and \( H(z) \) is the transfer function of the linear system that is predicted.

The model order indicates the number of poles of the AR model. It is an important parameter as it determines the amount of spectral information that can be predicted from the input data.

The most important advantages of Burg's method are the superior estimation of short data records and better resolution of closely spaced sinusoids with low noise, and small divergence of the PSD estimates from the true values. On the other hand, the accuracy of Burg's method is decreasing for higher model orders, longer data, and higher signal-to-noise ratios.

By assuming that short sections of data (10 up to 40 samples long) have deterministic autocorrelation sequences then we can use an AR method for spectral estimation. A sequence (in time) of PSD estimations is calculated. The sliding window size and the overlap between successive window positions define the number of PSD estimated required:

\[
\text{Number of PSD estimations} = \left\lfloor \frac{N_{\text{samples}}}{(N_{\text{window}} - N_{\text{overlap}})} \right\rfloor
\]
By concatenating these estimates the time-frequency representation of the whole signal is obtained. This representation is similar to the traditional spectrogram that is obtained by the Short-Time Fourier Transform method. Some examples of the PSDs of ECG signals in the t-f plane are shown here. The signal used in the examples was sampled with a frequency of 125 samples per second for a duration of 5 seconds resulting in 625 consecutive samples of a continuous signal. The figures show the effects of window size, overlap and AR order on the time and frequency properties of the spectrograms.

Figure 18 ECG Signal segment in time-domain. Sampling frequency=125 S/s

Figure 19 AR spectrogram with Window=10 samples, Overlap=2 samples, AR model order= 2

Figure 20 AR spectrogram with Window=10 samples, Overlap=9 samples, AR model order = 2.
As it can be observed from the examples above, while the window size increases and the overlap remains constant (5 samples), the time resolution is getting poorer. On the other hand, higher AR model order calculates more AR parameters (coefficients) and thus more detailed spectral information is predicted from the input signal.
2.4.2 Statistical Images

Additional information needed for the analysis of ECG signals was derived from the variance, standard deviation and mean image of the spectrogram. These measures improve the noise robustness of the method used for the purpose of the artifact detection and removal. The three statistical images are calculated by processing the spectrogram image using a 15x15 neighborhood window that runs over the entire image. For each neighborhood the variance, standard deviation and mean are calculated. The center element (pixel) in that window defines the location of the value that the new image will have after processing. The moving window centers sequentially over all the elements of the image, with the maximum possible overlap. For the cases of the elements at the borders, the window considers only the existing pixels for the calculations, that is, no padding is being performed. We hence obtain three images (Variance, Standard Deviation and Mean) of the same size of that as the spectrogram image. It should be noted that there is the potential advantage of processing only a certain part of the spectrogram, i.e. choosing a certain frequency band, and obtaining statistic images from a specific area of the spectrogram. In Figure 25, an example of a Burg’s spectrogram and the three statistic images are shown.
The decision for the size of the window (15x15) was taken after extensive experimentation, and in combination with the other parameters such as the Burg’s window and overlap and the AR model order. Other square window sizes, that were examined in order to find the optimal combination, were windows of sizes: 5, 11, 21 and 31. Additionally, again after experimentation, it was determined that the most useful statistical image was the **Mean Image** since it yielded superior results over the other two for the artifact detection. Thus it was used for the rest of this work.

### 2.4.3 Otsu’s Automatic Threshold

Automatic thresholding was necessary in two cases: (i) for detecting the level that optimally separates the spectral value populations in the Mean Image and (ii) for detecting the QRS complexes. Otsu’s automatic threshold finds the level which optimally separates two populations. Otsu’s algorithm assumes that the data is separated in two populations or classes. Then it exhaustively searches for the threshold that minimizes the intra-class variance or maximizes the inter-class variance, which Otsu shows that are the same. Therefore, it finds a threshold that separates the two classes their combined spread (intra-class) is minimum [36,37]. This method was used to convert gray scale images, with values in the range of [0,1] into binary images of **true (1)** or **false (0)** values. True values yield are assigned to the pixels that their value exceeds the threshold level and false values to those which are less than the level.
2.4.4 Morphological Processes

The algorithm for artifact detection should detect only the areas that contain artifacts, that is, the group of pixels with high frequency spectral content. It is assumed that these areas occupy relatively wide areas in time. Narrow components like the heart beats must be removed from the binary image in order to detect the artifact area more accurately. For this purpose two operations were performed: morphological image closing and opening.

The first operation was the Morphological Image Closing which fills in small breaks, holes or gaps in the horizontal direction, with width size less than 7% of the sampling frequency. This operation was performed in order to create solid objects not separated by such small gaps. Right after closing, the Morphological Image Opening filter was applied on the image to eliminate small objects in the horizontal direction, whose width (duration in time) was less than 30% of the sampling frequency. This means that objects less than ~0.25s were rejected. Note that the normal QRS complex duration is around 0.1s but in the binary image the components are sometimes wider than the actual ECG in time due to the use of windows which smooth the components and sometimes spread them out. Morphological opening performs an erosion and then dilation on the image using the same structuring element for both, while morphological closing performs a dilation followed by erosion using again the same structuring element [38]. An example is given in Figure 26.
Figure 26 (A) The annotated ECG signal in time. Red annotations show the R-peak, green indicates the Q-wave and the yellow lines indicate the end points of the artifact area. (B) The Mean Image of the spectrogram of the signal in A. (C) The binary image of the spectrogram using automatic threshold. (D) The binary image after morphological closing in horizontal direction where the small gaps are getting filled in. (E) The binary mask of the artifact obtained after morphological opening of the image in D in the horizontal direction. The first three objects (heartbeats) were rejected due to their small width.

2.4.5 Other Methods

Linear Interpolation
An important step before the calculation of the Burg’s spectrogram was to fill in some of the missing points in the ECG data. Those missing values are shown as Not-A-Numbers (NaNs) and are presented as gaps when displayed in Matlab. These gaps usually have a relatively short duration and they can be filled in by using 1 dimensional (1D) linear interpolation [39].

Logarithmic Scaling
The amplitude of the two-dimensional time-frequency representation, obtained after the application of Burg’s method onto the original signal, was compressed
in logarithmic scale. The pixel intensity values initially represented the spectral power. The conversion of the pixel intensity values from spectral power units into Decibels was performed with the following relation:

\[
I_{\text{new}} = 10 \log_{10}(I_{\text{initial}})
\]  

(T-Test)

A t-test was performed in order to find and preselect a threshold above which a number of 1s in the binary image indicated the presence of artifact in the signal [40]. Briefly, the t-test indicates if and how well, two datasets can be separated according to their means and variances.
CHAPTER 3
DESCRIPTION OF THE ALGORITHM

3.1 General Algorithm

Description

1. Load the ECG signal (X) from the database with the annotated signals.
2. If there are any missing values (Not-a-Number-s) interpolate to fill in the gaps.
3. Run the algorithm Artifact Hypothesis Testing to decide whether the signal contains artifact or not.
4. If the Artifact Hypothesis Testing is NO then go to step 6. If the decision is YES then the next step is 5, the Artifact Detection and Removal.
5. The Artifact Detection and Removal algorithm is executed when there is an artifact area in the data.
6. The artifact-free signal (either normal or cleaned) is processed in order to find the QRS complexes.
7. Comparison of the algorithm’s results with the manual annotations derives the percentage of the correctly classified QRS complexes.
3.2 Description of the main blocks of the algorithm

3.2.1 Artifact Hypothesis Testing

The purpose of this procedure is to correctly decide whether there is an artifact in the ECG signal or not. The algorithm is shown and described below.
1. Calculate the time-frequency representation of the signal using Burg's method with the following parameters:
   a. Burg’s window: 15 samples
   b. Overlap: 5 samples
   c. AR model order: 2
   d. $N_{\text{FFT}}$: $2^{10}$

2. Use only the part of the spectrogram from 55 to 60Hz. (The band choice was a result of the observation that most of the PSD of the artifact was in the high frequency part of the spectrogram).

3. Convert the spectrogram to a binary image using Otsu’s automatic threshold.

4. Perform morphological opening in the horizontal direction of the binary image, in order to eliminate objects with a width less than 30% of the sampling frequency.

5. If the number of 1s (true values) was greater than 150 pixels, then the hypothesis is that artifact exists in the image (YES), otherwise the hypothesis is that the signal does not contain artifact (NO).

It must be noted that the spectrogram’s parameters and the threshold (150 true values) for optimal detection of artifact presence in the image were found experimentally, with the help of t-test (see section 2.7) to optimally separate the images with and without artifact.
3.2.2 Artifact Area Detection
Artifact detection is an important step in automatic QRS detection. The purpose of this algorithm is to detect accurately the area of the artifact. Ideally, the signals that reach this step do contain artifact, based on the decision of the previous step (Artifact Hypothesis Testing). The output of the code for “Artifact Area Detection” is a binary mask with pixel values set to 1 if they correspond to artifact, and 0 everywhere else. The flowchart of this block is shown below.
Description

1. Calculate the time-frequency representation of the signal using Burg’s method with the following parameters:
   a. Burg’s window: 15 samples
   b. Overlap: 10 samples
   c. AR model order: 2
   d. $N_{FFT}$: $2^{10}$

2. Calculate the Mean Image with a 15x15 neighborhood. The frequency band chosen was again that between 55 and 60 Hz where the artifact has greater power than the other components of the signal.

3. Convert the Mean Image to a binary image using Otsu’s automatic threshold.

4. Perform morphological operations, first closing and then opening, to eliminate the objects, such as heart beats, that are not artifacts but represented in the binary image as 1s. As it was mentioned before, these objects are significantly smaller than the artifact area, so that they can be effectively removed from the binary image (see 2.4.4 Morphological Processes).

5. The output of the algorithm is a binary image, called an “Artifact Mask”. The pixels corresponding to the locations of artifact have the value 1, whereas everywhere else, the value is 0.
3.2.3 Artifact Removal

A very simple idea has been implemented, for removing and not considering the artifact in the subsequent processes of QRS detection. Each spectrogram, which contains the artifact, is multiplied by the logical complement of the artifact mask.
The multiplication is performed element-wise and in a spectrogram where the area of artifact has been converted to 0s. An example is given in Figure 30.

![Figure 30](image)

*Figure 30 (A) ECG signal with artifact. The green vertical lines indicate the manually marked endpoints of the artifact area. The red vertical lines indicate the automatically detected artifact area endpoints. (B) The Artifact Mask. Red indicates logical values of one and blue logical zeros. (C) Spectrogram Image. Red corresponds to high spectral power while blue corresponds to low power. (D) The artifact-free spectrogram image. Blue corresponds to zero values.*

### 3.2.4 QRS Complex Detection

The detection of the QRS complexes is an important part of automatic ECG monitoring while, at the same time, useful information regarding heart functionality can be extracted from those same complexes. The level of the positive predictivity of an automatic QRS detector is important as it may affect the quality of the diagnosis of cardiac and other diseases or abnormalities. QRS complex detection is the last step of the proposed algorithm. Artifact-free signals reach this step directly, while artifact-containing signals undergo artifact detection and removal first.
Start

**Input:** A=Artifact-Clean Spectrogram

**Input Data:**
X=ECG Signal in time
f1=5Hz
f2=20Hz

Summation of the image's values in the vertical direction in Frequency Range [5,20]Hz
Y=sum(A);

**Normalize Y:** Y∈ [0,1]
Y=Y-min(Y);
Y=Y/max(Y);

Calculate Automatic Threshold Using Otsu's Method

P=Find the locations of the peaks in Y with higher height than the threshold

R locations=search in locations P±8 to find maximums in X.
Q locations= search locations R-10 for minimum in X.
S locations=search locations R+10 for minimum in X.

Output:
QRS locations

END

*Figure 31 Flowchart of the QRS complex detection Algorithm.*
1. Calculate the time-frequency representation of the signal using Burg’s method with the following parameters:
   a. Burg’s window: 10 samples
   b. Overlap: 5 samples
   c. AR model order: 2
   d. N_{FFT}: 2^{10}

2. Sum the spectral values between 5 and 20 Hz at each time point.

3. Normalize the summed data between [0,1].
   \[ Y = Y - \text{minimum} \ (Y); \]
   \[ Y = Y / \text{maximum} \ (Y); \]

4. Calculate the automatic threshold for the vector \( Y \), using the Otsu’s method to separate the peaks that correspond to QRS complexes from noise.

5. Find the peaks of the \( Y \) vector with higher height than the “level” of the threshold and get their locations.

6. Map the above locations into the ECG signal (X) and find the peaks, i.e. the R peaks, in a range of ±8 samples around each maximum location.

7. Find the Q-wave and S-waves by finding the minimum peaks in the range of -10 and +10 samples around each R respectively.

**Description**

The input for this block is an artifact-free spectrogram. The frequency band, selected for QRS complexes detection, was between 5 and 20Hz. That range was selected since the QRS waves have high spectral content at these frequencies, while the DC and low frequency, below 5Hz, as well as the high frequency noise and much of the artifact power are avoided. An example of the results of the algorithm is shown in Figure 32.
Figure 32 Picture A: A normal ECG signal without artifacts in it. Picture B: the spectrogram image. The red rectangle indicates the part of the image processed (frequency band 5-20Hz). Picture C: the plot of the summation (normalized in [0,1]) of the values in each column of the spectrogram is thresholded. Picture D: an overlay of the summation data and the ECG signal. The red peaks are yielded from the summation and the blue from the signal. The peaks of the red graph approximately coincide with the R-peaks of the signal. In the last picture the Q, R and S waves were automatically detected and noted.
CHAPTER 4
RESULTS & DISCUSSION

A dataset of 45 ECG segments were chosen randomly from eight different ICU patients from the MIMIC II database. Each segment lasted from five to ten seconds. Twenty of the data segments, that were manually annotated and then used in the experiment, contained various types of artifacts of different durations. Another twenty pieces contained only normal QRS complexes and the remaining five sets contained some abnormal beats in addition to the normal QRS beats. Tables with detailed description can be found in the APPENDIX A.

4.1 Results of the proposed method

4.1.1 Artifact Hypothesis Testing Results

The Artifact Hypothesis Testing algorithm was used to decide whether the signal under consideration contained some artifact or not. Based on this decision, the signal was classified as Artifact or Normal and was further processed to remove the artifact if it belongs to the first category. Hence, this was an important step for achieving more accurate results in the QRS detection step. Table 1 shows the results of the application of this algorithm on the 45 ECG segments.

<table>
<thead>
<tr>
<th>ACTUAL</th>
<th>ESTIMATED</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Artifact</td>
</tr>
<tr>
<td>Artifact</td>
<td>18</td>
</tr>
<tr>
<td>Normal</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>18</td>
</tr>
</tbody>
</table>

Table 1 Results of the classification of the signals into the classes Artifact and Normal.
Of the 20 signals that actually contained artifacts, 18 signals were classified correctly whereas 2 of them classified as Normal signals. All of the 25 signals in the Normal category were classified into the correct class. Thus:

Correctly classified (%) = (43/45) * 100 = 95.56%

The two signals that were wrongly classified as artifact-free are shown below. The artifact in both cases is missing data that was filled in using interpolation (see section 2.4.5 Other Methods). Although not detected, these artifacts do not significantly affect the performance of the QRS detection, since as it turns, out do not yield significant false negative or false positive results. Examples of other types of artifacts are shown in the next section.

4.1.2 Artifact Detection and Removal Results

The Artifact Detection and Removal algorithm was applied to signals that were classified, during the previous step, as artifact-containing signals. This algorithm results in three cases, after the detection of the artifact:

1. Whole artifact area detection and removal without cutting off any other parts of the signal which might contain QRS complexes.
2. Detection and removal of a part of the artifact while a portion of the artifact still remains in the signal.
3. Detection and removal of a bigger area than what the artifact covers. This might remove some QRS complexes if they exist in the area wrongly identified as artifact.

In order to evaluate the performance of the algorithm, its results were compared to the manually annotated data. If a point was classified as artifact and was in the actual artifact area was considered a True Positive, otherwise it was considered a False Positive. Similarly, True Negatives and False Negatives were calculated from points classified as not-artifact. The overall accuracy of the artifact detection algorithm, after testing on the 18 ECG signals that were identified as artifact-containing in the previous step was:

Correctly Classified Area (%) = 95.60%.
Misclassified Area (%) = 4.40%.

Table 2 Results of Artifact Detection Algorithm

<table>
<thead>
<tr>
<th>ACTUAL</th>
<th>ESTIMATED</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Artifact</td>
</tr>
<tr>
<td>Artifact</td>
<td>29.89%</td>
</tr>
<tr>
<td>Not Artifact</td>
<td>2.74%</td>
</tr>
</tbody>
</table>

Some examples of the three cases mentioned previously, are shown below. In the first case (Figure 35), the algorithm successfully detected the whole area of the artifact accurately, without cutting off any other important information such as QRS complexes. In this case the correctly classified artifact area was 99.19%. The green vertical lines indicate the manual annotations while the red vertical lines indicate the estimated artifact area.
The second case illustrates the detection and removal of a part of the artifact while some part of it, still remained in the signal (Figure 36). In this case the correctly classified artifact area was 87.90%. The green and red vertical lines indicate manual annotations and estimated area respectively of the end points of the artifact. The estimate misses part of the artifact (between the red arrows) and, as a result, the subsequent step in the algorithm detects a QRS complex in the area marked B. In the case of area A, although the algorithm incorrectly classifies it as not-artifact, no QRS complexes were detected there.

The last case is that of detection and removal of a bigger area than what the artifact covers (Figure 37). As a consequent, a QRS complex was cut off (Area A). As before, the green lines indicate the manually annotated extend of the artifact whereas the red lines demarcate the extend based on the automated algorithm. In this case, the correctly classified artifact area was 90.24%. Even though an
area is cutoff on the right as well (Area B), this does not affect the QRS detection since it does not include any QRS complexes.

![Unwanted cut off of a QRS complex in area A.](image)

**Figure 37** Unwanted cut off of a QRS complex in area A.

### 4.1.3 QRS complex Detection Results

The QRS detection algorithm is the last step of the proposed algorithm and aims to detect the QRS complexes in an ECG signal. The test performed was performed on all 45 ECG segments. Some of them contained abnormal beats (ECG events) as well. Ideally those events should also be recognized as QRS complexes. The results are presented in the Table 3.

<table>
<thead>
<tr>
<th></th>
<th>True Positives</th>
<th>False Negatives</th>
<th>False Positives</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal Segments</td>
<td>173</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Artifact-containing Segments</td>
<td>113</td>
<td>6</td>
<td>13</td>
</tr>
<tr>
<td>Abnormal Event Segments</td>
<td>36</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td>Overall</td>
<td>322</td>
<td>13</td>
<td>15</td>
</tr>
</tbody>
</table>

Table 3 Results of QRS complex detection.

\[
Correct\ Classification(\%) = \frac{TP}{TP + FN + FP}
\]

Overall

The overall percentage of correct classification of the beats reached 92%. The overall number of the registered (manually annotated) QRS complexes was 335
of which 322 were detected correctly (True Positives), and 13 were missed (False Negatives). In addition, there were 15 beats wrongly detected as QRS complexes (False Positives).

**Normal Segments**
The results from the 20 signals that contained only normal QRS complexes resulted in a QRS detection of 100%. A total of 173 registered QRS complexes were all correctly classified, while neither False Positives nor False Negatives appeared.

**Artifact-containing Segments**
QRS detection in the 20 signals that contained artifact (18 of those had it removed), resulted in a correct classification of 85.6%. Of the total of 119 marked beats, 113 were detected correctly (True Positives), along with 6 False Positives and 13 False Negatives.

**Abnormal event Segments**
Signals that contained abnormal beats plus the two signals that contained artifact but were not recognized by the Artifact Hypothesis Test, resulted in a correct QRS classification of 80%. From a total of 43 beats, 36 were correctly classified (True Positives), 7 were False Negatives and 2 were False Positives.

The following figures graphically illustrate the notions of correct classification (TP) and misclassifications (FP and FN).
Figure 39 The failure to recognize and remove the artifact caused false detection of two QRS complexes (FP).

Figure 40 Two QRS complexes were missed (FN) by the algorithm due to the removal of bigger than the actual artifact area.
4.2 Results from a Wavelet-Transform method

In this section, the same ECG data as before was analyzed with a commonly used Wavelet Transform Analysis (WTA) based algorithm for comparison purposes. This algorithm is used for QRS detection using WTA and is described in detail in the literature [23,41,42]. Below is a brief description of the steps followed for the implementation of the multiscale based algorithm:

1. Wavelet Transformation of the ECG signal for the first four scales
2. Calculation of the RMS values for the interval of every consecutive QRS complex.
3. Find the local maxima that exceed the threshold found from the step 2.
4. Zero Crossing between a pair of positive maximum and negative minimum of the Wavelet Transform of the 1st scale is detected as a QRS.

The results of the application of the WTA algorithm, on the same ECG data, are summarized in Table 4:

<table>
<thead>
<tr>
<th></th>
<th>True Positives</th>
<th>False Negatives</th>
<th>False Positives</th>
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<tr>
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<td>6</td>
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<td>Artifact-containing Segments</td>
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<td>40</td>
<td>101</td>
</tr>
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<td>Abnormal Event Segments</td>
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<td>14</td>
<td>12</td>
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<tr>
<td>Overall</td>
<td>279</td>
<td>56</td>
<td>119</td>
</tr>
</tbody>
</table>

**Overall**

Examination of all the 45 datasets of all the classes yielded a correct classification rate of 65.30%.

**Normal Segments**

Applying the algorithm only to the 20 signals that contained only Normal QRS complexes the correct classification reached 96.19%.
Artifact-containing Segments

QRS detection in only the 20 signals that contained artifact gave 38.36% correct classification.

Abnormal event Segments

Signals that contained abnormal beats plus the two signals that contained artifact but rejected by the Artifact Hypothesis Test resulted in a correct classification of 49.47%.
4.3 Discussion

Starting from the most important results, those for the QRS detection, it is evident that the proposed algorithm is very successful in this task. It is also obvious that the results are significantly affected by the presence of artifacts an issue alleviated to a large extend by the artifact detection and removal algorithm. The proposed algorithm yields an overall score of 92% correct classification. Particularly, if the signal contains only normal QRS complexes the QRS complexes are 100% correctly classified although the performance is poorer for signals with artifacts and abnormal beats (85% and 80% respectively). However, this performance is still substantially better than that of the commonly used – Wavelet-based QRS detection algorithm. On the same data set, the overall correct beat detection of that algorithm was only 65.30%. Given that on normal ECG signals the wavelets perform very well (96,2%), it becomes clearly evident that artifacts or abnormal beats significantly degrade the performance of the algorithm (38,36% and 49,47% correct classification respectively).

The performance of the proposed algorithm is significantly improved because of it artifact testing, detection, and removal features. The results from the first step (Artifact Hypothesis Testing) showed that signals which did not contain artifact were all classified correctly. The limitation of this step was mainly the misclassification of signals with missing data artifact or saturations. This is not tragic since these kinds of artifacts can be detected at an earlier step while the signal is interpolated for filling in the missing data. At this step, a decision can be made that the signal contains artifact and it can be removed at the same. Another limitation might be the preselected threshold that has been used here.

Artifact Detection is an important step in minimizing the False Positives in QRS detection in the case of artifact containing signals. However, the artifact area has to be detected as accurately as possible in order to not only avoid the False Positives but to limit the False Negatives as well. Ideally there should not be much divergence between the detected edges and those of the actual area. This
problem can be minimized with appropriate adjustments of the parameters of the Burg's method for calculating the spectrogram. For instance, a narrow Burg's window and increased overlap provide higher resolution in time. Moreover, the window used for calculating the statistical images can be adjusted similarly. The automatic threshold is another factor that affects the accuracy of the detection. In this case, a database of such thresholds can be developed so that the algorithm could be somewhat trained on accepting or rejecting accordingly.

For the results of this study to be generalized, a much larger data set is needed. In that way there will be a much larger and more varied number of cases so that the statistical conclusions can be drawn safely. An important parameter that could possibly affect the results is the accuracy of the manual annotations. In that case, more than one annotators should be used to validate the annotations between them.
CHAPTER 5
CONCLUSIONS & FUTURE WORK

In conclusion, a method based on Time-Frequency Analysis was developed in order to automatically analyze ECG data. This analysis included algorithms for:

a) Decision for artifact presence in the signal
b) Artifact area detection and removal
c) QRS detection (Normal and Abnormal beats)

The proposed method yields 92% correct QRS detection, in contrast with the commonly used Wavelet Transform analysis (WTA) method, which gives around 65.30%. The improved performance of the proposed method is a result of the detection and removal of ~96% of the artifact, when it exists in the signal, thus avoiding the majority of possible false detections. To our knowledge, this is the first case where artifact detection and rejection in ECG signals have been so successfully implemented.

Future Work

Besides the suggestions mentioned previously (4.3 Discussion), in the future this work could be extended as an ECG-based, automated diagnostic tool for various diseases of the cardiovascular system. More work is necessary in order to detect the P and T waves as well, which provide additional information about specific functionalities of the heart. Of course, additional research leading to successful detection and classification of the various types of abnormal beats will be the hallmark of the success of this algorithm as a diagnostic tool.
REFERENCES


[38] MATLAB Documentation: http://www.mathworks.com/help/toolbox/images/ref/f3-23960.html#f3-22980

[40] MATLAB Documentation


## A.1. Artifact Hypothesis Results (1→True, 0→False)

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### A.2. Artifact Detection Results

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<th>Pat.No / BeginT</th>
<th>True Positives (%)Area</th>
<th>True Negatives (%)Area</th>
<th>False Positives (%)Area</th>
<th>False Negatives (%)Area</th>
<th>Correct Classification (%)Area</th>
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### B. QRS Detection Results

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### B.2. Wavelet Transform Method
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