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Applied Mathematics and Informatics Program

Mathematical Model
in Acute Cardiac Ischemia Evaluation

Moritz M. Konarski

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Author
Moritz M. Konarski

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Certified by Thesis Supervisor
Professor Taalaibek Imanaliev

_____

Accepted by
Sergey Sklyar
Head of Applied Mathematics and
Informatics Program, AUCA

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TABLE OF CONTENTS

1   INTRODUCTION

In the year 2016, over 9.4 million people worldwide died of ischemic heart disease (IHD). IHD is responsible for 16.6% of all deaths, making it the most common cause of death globally. Considering all forms of cardiovascular disease, the percentage of deaths attributed to it is 31.4% (17.9 million deaths). Death caused by IHD disproportionally affects people over 50 years of age, with 91% of deaths for men and 95% of deaths for women occurring in that age range. In Kyrgyzstan, 13% of all deaths in 2016 were caused by IHD [1].

Ischemic heart disease is characterized by restricted blood flow to an area of the heart, causing it to not receive enough blood and oxygen. Blood flow restriction is caused by a blockage (or narrowing) in a blood vessel supplying the heart muscle. An artery can be blocked by a blood clot, but the most common cause is plaque buildup, which is called atherosclerosis. If the circulation to the heart is completely blocked, the cells in the heart muscle begin to die. This is called myocardial infarction, more commonly known as a heart attack. The deprivation of oxygen the heart experiences leads to the characteristic chest pain commonly associated with heart attacks [2].

IHD can be diagnosed before it leads to a heart attack. The diagnosis can be performed based on a patient's medical history, pharmacologically induced stress, or stress induced by physical exercise. During an exercise stress test, an electrocardiograph (sometimes combined with other methods) records the patient's heart activity, resulting in an electrocardiogram (ECG) [2]. The ECG is a diagnostic tool used to evaluate patients with (suspected) heart problems. It is a non-invasive and cost-effective method that may be used to diagnose IHD. It is the most common tool used for cardiac analysis and diagnosis [3, 4, 5]. The most common form of the ECG is the 12-lead variant. The 12-lead ECG consists of 6 leads connected to the limbs and of 6 leads connected to the torso of the patient. Together, the leads record the differences in potential between the places on the body that the leads are attached to. They reflect the differences in voltage that the heart experiences with each heart beat because those voltage differences are conducted by the body. In a way, the ECG represents the state of the heart [4, 5]. If the nature of the heart beat changes as the result of a disease like IHD (changing the measurable potentials or their occurrence over time), the ECG is able to record these changes.

The diagnosis of diseases using an ECG is difficult in practice. Small changes in the ECG can be indicators of diseases and they can be missed, even by trained and specialized physicians. The error chance is even higher for non-specialized physicians and trainees [3, 5]. Especially in the case of IHD, the diagnosis on the basis of an ECG is time sensitive. If a patient has IHD or suffers from a heart attack, treatment has to be started as soon as possible. Some forms of treatment are most effective in the first 3 hours after symptom onset and lose most of their effectiveness after 9 to 12 hours. The diagnosis required for treatment to begin should thus be as quick as possible. The real-time nature of the ECG is an advantage here, even though more time consuming methods can deliver more accurate results [6].

The widespread use of ECGs and the time-sensitive nature of their application as diagnostic tools makes errors, delays, or inconsistencies in their interpretation are not acceptable. A recent

approach to minimizing this problem is the application of computer technology to the recording, storage, and analysis of ECGs. The main steps of computerized ECG analysis are [4]

1) signal acquisition and filtering,
2) data transformation or preparation for processing,
3) waveform recognition,
4) feature extraction,
5) classification or diagnosis.

This research plans to investigate steps 3) and 4) through the use of different feature extraction algorithms. The ECG data used will come from the MIT-BIH Normal Sinus Rhythm Database for normal ECGs [7, 8] and from the European ST-T Database for ECGs of patients with IHD [7, 9]. Both databases provide ECG recordings that can be used as trial data to test feature extraction algorithms. The European ST-T Database furthermore contains annotations by cardiologists indicating the significant changes in the ECG as well as the suspected disease and its severity. This information can be used to determine the effectiveness of the feature extraction algorithms.

2 METHODS AND ALGORITHMS IN ELECTROCARDIOGRAPHY

Recent advances in computer technology have enabled the widespread use of computers in every aspect of ECG acquisition, processing, analysis, and storage. In light of these developments, the American Heart Association published a series of 6 papers with recommendations for the interpretation and standardization of the ECG. They address issues of ECG sampling, signal filtering to remove distortions, and detection of the relevant features and complexes. For each of the points they provide recommendations to maximize the usefulness and accuracy of the ECG [4].

The standard approach to using computerized methods in ECG analysis is to select a filtering algorithm to remove distortions, choose a method for feature recognition and extraction, reducing the number of irrelevant features, and a method for classification. Common methods for signal filtering and noise removal are digital filtering, application of the wavelet transform, and empirical mode decomposition. Feature recognition methods include the Fourier Transform, Fast Fourier Transform, short-time Fourier Transform, wavelet analysis, and statistical methods. Methods for feature extraction include principal component analysis, linear discriminant analysis, independent component analysis, and generalized component analysis. Where before decision trees and boolean conditions were used for classification, learning algorithms are now becoming more popular. These algorithms have the advantage that they are adaptive and can react to changes in the input data and they do not need to manually preselected or preconfigured to the same extend. The newest trend takes a different approach. Instead of splitting the ECG analysis into denoising, feature extraction and selection, and classification, it proposes to apply a single, large artificial neural network to the raw data. This end-to-end model will then complete all the steps that had to be individually tuned before. It will denoise the data, select the appropriate features, and classify the result [5].

Myers, Scirica, and Stultz [10] utilized an artificial neural network based on ST-segment features to create a risk model that can augment other clinical risk scores. Their model uses machine learning to extract more information from an ECG than is generally available to a human analyst.

Prasad and Parthasarathy [11] use a median filter to denoise the ECG, then the fast Fourier Transform to extract features and finally a multi-objective genetic algorithm to detect abnormal ECG signals with 98.7%.

Goto, Kimura, Katsumata, *et al.* [12] trained an artificial intelligence model to recognize the need for urgent revascularization. Their model achieved high accuracy based on their training data set.

Vaneghi, Oladazimi, Shiman, *et al.* [13] compare 6 common feature extraction techniques with respect to their detection of ventricular late potential. The compared methods are the autoregressive method, wavelet transform, eigenvector, fast Fourier Transform, linear prediction, and independent component analysis. They conclude that the eigenvector method is the most effective method.

Maršánová, Ronzhina, Smíšek, *et al.* [14] compare the most frequently used classification functions for ischemic heart beats. The functions are discriminant function analysis, naive Bayes

classifier, support vector machine, and k-nearest neighbours. They found that k-NN and RBF SVM are the most suitable. This coincides with existing literature.

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