Identification of Myocardial Infarction by High Frequency Serial ECG Measurement

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Abstract

The purpose of this study is to attempt to identify acute myocardial infarction with high frequency serial electrocardiogram which both are ECG analyzing techniques. The idea is to combine these two techniques and see if changes between different ECGs from the same person can provide us with some information, whether it being in the high frequency or normal frequency range of ECG. A heart attack can occur at any time and therefore the possibility of using a wearable device was also researched.

To answer the questions, an existing database which contained multiple ECGs for each person with high sampling frequency was used. On top of this, a new serial ECG database was gathered using a wearable device designed by the University of Turku. Using multiple ECGs, features were extracted from the signals and then used in different machine learning methods in order to classify the subjects.

All of the methods seem to be relevant. High frequency ECG was found to be useful, while serial ECG provided us good results with both databases. The device was also found to be able to produce good quality ECG.

1. Introduction

Acute myocardial infarction (AMI) is one of the main reasons of death all over the world [1-2] More commonly known as the heart attack, AMI is usually detected with electrocardiogram (ECG) [3]. While ECG is one of the most essential parts of medical care [3], it can suffer from low diagnostic accuracy [2]. The nature of ECG can cause a significant variability in the ECG between patients [4] creating a problem when analysing the signals.

One way to prevent this problem would be serial electrocardiogram (S-ECG). It is a promising method in which, different ECGs from the same patient are compared in order to overcome the problems with a singular ECG recording [5]. With this method, the variability between the patients should be disposed and the focus can be placed more on the intraindividual variability [4]. S-ECG has been found to improve the performance when detecting AMI, compared to the initial ECG [2,6].

Previous studies suggest that regular measurements done with S-ECG, would be beneficial detecting AMI [7]. The technique is best suited for symptom-based measurement. If you feel unwell, you can take a measurement to determine whether you are suffering from AMI or not. However, visiting the hospital regularly to measure your ECG just for monitoring can be time consuming and expensive. For this reason, a small wearable device to measure ECGs is suggested. With this device, the patient can measure ECG at home by himself.

Another method used in this paper is high frequency ECG (HF-ECG). It has been suggested to be more sensitive detecting acute coronary artery occlusion than the standardly used ST-segment deviation [8]. While normal ECG is usually filtered between 0.5-25 Hz, HF-ECG is considered to consists between 150-250 Hz [8]. While being a rather unstudied subject, there isn't any standard methods while working with HF-ECG.

In this study, the aim is to determine if S-ECG is able to detect AMI, if a wearable device can be used for AMI detection and if HF-ECG content can provide more insight of the myocardial health.

2. Material and methods

2.1. Data

The database used in the study was the STAFF III database from 1995 [9]. The database consists of 104 patients, who all have multiple ECG recordings. In this study, 3 recordings from every patient were used. 2 of them are baseline recordings, first recorded in a relaxing room, while the second ECG is recorded in a catheterization laboratory also relaxed, just before the most significant recording. The inflation ECG is measured while the patient is having prolonged angioplasty. This makes the database significant and unique since the ECG is recorded while suffering from emulated AMI. Another unique feature of this database is its sampling rate of 1000 Hz and wide analog bandwidth. This allows us to extract HF-ECG features.

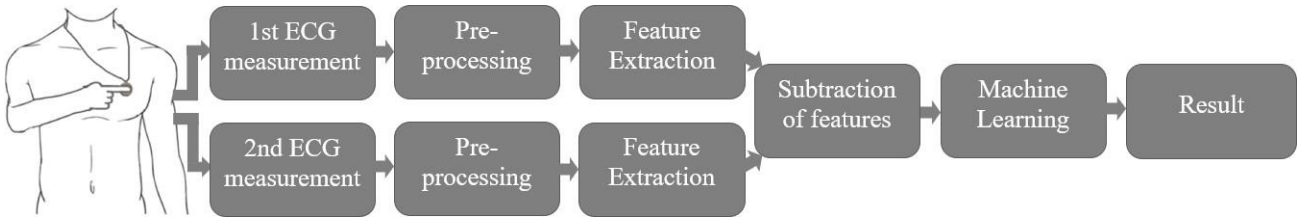

Figure 1. Block diagram of the classification process for S-ECG with the SAFE device. Two ECGs are recorded, after which the signals are handled accordingly. The ECGs were measured as shown in the graph, the right index finger on the other lead while pressing the second lead of the device into the chest. Measurements were done in a resting position.

From the database, 94 of the subjects were able to be used for the study. Since the nature of S-ECG, a healthy variant and a sick alternative were produced. Healthy cases included S-ECG of the two baselines, while the sick cases included S-ECG of one baseline and one inflation recording. This created a dataset of the size of 188 subjects, split equally between healthy and sick.

To determine if a wearable device is a plausible method to detect AMI, data gathered with such a device was needed. For this step, device called SAFE, developed by the University of Turku, was used. It can record single channel ECG with 512 Hz sampling rate. The device consist of a Movesense medical device [10] created by Suunto, a casing done with a 3D printer and two copper leads. The Movesense medical device has been classified as a Class IIa medical device [10]. A measurement can be done by pressing the two copper leads simultaneously. With SAFE, S-ECG data was able to be gathered from 10 subjects, meaning that every subject had their ECG measured twice. The time interval between the measurements varied from 1 hour to 1 week. All of the patients were in good health and had no reported heart diseases. The age of the patients varied from 19 to 52.

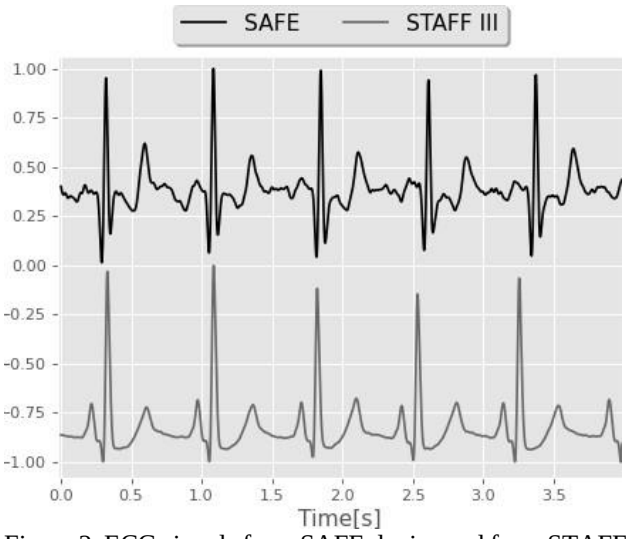

Figure 2. ECG signals from SAFE device and from STAFF III database. The signals are fairly similar, SAFE signals are not as smooth as the STAFF III signals but contain the QRS-complex, T-wave and some even the P-wave. It can be concluded that the ECG gathered with SAFE has good enough quality to be used.

2.2. Algorithms

To get a classification for an ECG measurement, multiple different algorithms have to be applied to the signal. Figure 1 represents this process. First, two ECGs are recorded. Time interval between these recordings can vary. Then the ECGs are imported into Python, where the pre-processing of the signals can start. This includes filtering the signal with a Butterworth band-pass-filter of 0.5 Hz to 25 Hz for normal ECG features and of 150 Hz to 250 Hz for the HF-ECG features. After this, the ECGs are normalised in order to reduce intraindividual variability and the differences between different measurement devices. This means scaling all of the signals between 0 and 1, based on the maximum and minimum values. For the SAFE database results, the signals are also resampled to 500 Hz. This is because the difference in sampling frequencies could affect the results of the HF-ECG features and every possible variant need to be considered and excluded. The signals were also visually inspected in case of motion artifacts or other abnormalities. Bad signals were removed from the databases. Figure 2 represents the pre-processed normal ECGs for both SAFE and STAFF III database.

After pre-processing, features from the signals can be extracted. From every signal, 16 features from both time and frequency domain are extracted. All feature extractions are done with our algorithms. These features are based on the most common ECG features, such as P- and T-waves and the QRS-complex. For example, we determine the R-peaks, with our algorithm based on the Pan-Tompkins, after which the heart rate and heart rate variability values can be calculated for the patient based on the R-peaks. PQ- and ST-segment values such as amplitude and length are also extracted. Also, statistical values from both domains were extracted.

After the features have been extracted, the two ECGs features are subtracted from each other. This means that ECG 1 features values are taken and then subtracted from that same feature value in ECG 2. After this the S-ECG

features have been calculated and can be inserted into the machine learning methods for classification and the result. For this study, five different machine learning methods were used in order to get the most accurate result.

3. Results

The mean results of the machine learning methods for both datasets are presented in table 1. Good results were achieved with the STAFF III database. For these results, the database with 188 subjects was used and split it into training and test set at the rate of 1:4. With cross-validation (CV), the best machine learning model reached the accuracy of 97,9%. CV can produce the most accurate results for accuracy in smaller datasets, since it uses all of the possible data when training the machine learning methods.

Table 1. Mean results of the machine learning models.

Database	STAFF III	SAFE
Size of the test set	47	10
Accuracy	91.9%	90.0%
Precision	95.5%	100%
Recall	88.9%	90.0%
F1 score	91.8%	94.0%
CV accuracy	94.6%	None

For the SAFE results, all of the 188 subjects of STAFF III database were used as the training set for the machine learning and then the SAFE databases subjects could be inserted as the test set. This produced good results as well. One of the SAFE patients was predicted as sick by all of the models, except one. With further inspection, the patient had abnormal heart rate variability values and the high-frequency content of the patient was irregular.

3.1. Data analysis

The principal component analysis in figure 3 represents the data in easily presentable and analyzable way. However, while it does give a good idea on how the data behaves, it does not perfectly present how the data works.

The figure demonstrates the differences between healthy and sick subjects. Healthy cluster seems to be tighter, while the sick cluster varies a lot more. The difference between sick and healthy also seems to be quite distinguishable. The SAFE patients also fit in nicely with the healthy patients. Few of them overlap with the sick cluster, but the orientation of the SAFE patients can be seen.

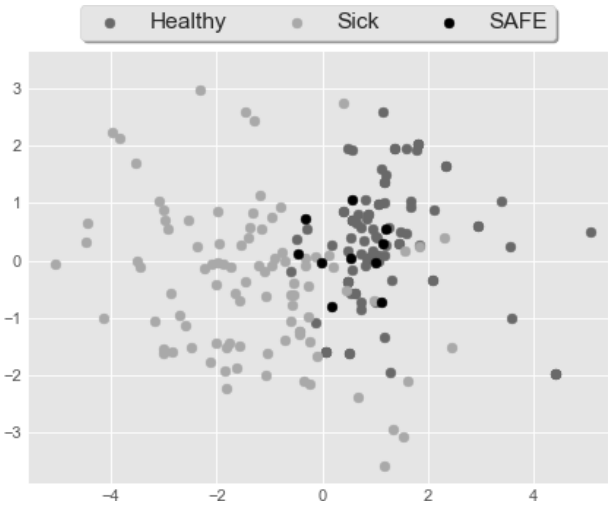

Figure 3. Principal component analysis (PCA) for the databases. PCA reduces dimensionality of the features and presents them in 2-dimensional space.

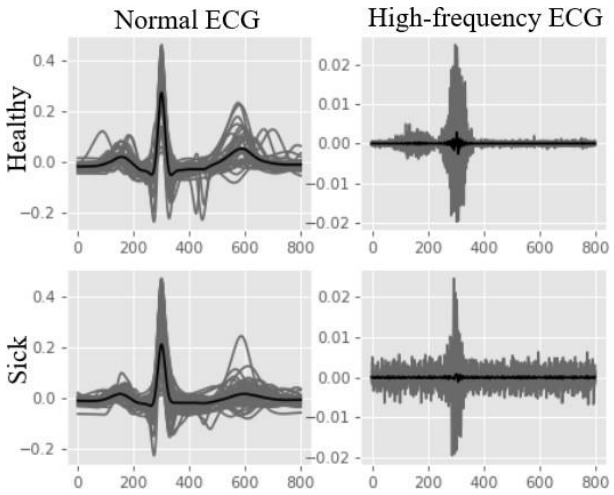

Figure 4. Average waveform based on R-peaks has been calculated for every ECG signal in STAFF III database. In this figure, the top row represents the healthy signals of both normal ECG and HF-ECG. Bottom row represents the sick signals averages. Each grey line represents one patient's average waveform, while the black lines represent the average of all the average waveforms.

In figure 4, the averages (black lines) in the HF-ECG graphs are irrelevant because the signals have such high frequency it dampens the average. In normal ECGs however the averages are relevant, and the figures show that the waveforms of them are rather similar. There are some changes in R-peak amplitude and in the ST-segment. The differences are however not that significant, but when looking at the HF-ECG averages and the grey lines, representing every patient's average waveform, it can be stated that the differences in healthy and sick are much clearer. The amplitude is higher throughout the sick

patient's averages and the R-peak is not as clear as in the healthy patient's averages. The P-wave is also not visible in sick averages. The sick HF-ECG signal seems to be showing more stress than the healthy HF-ECG. This and other HF-ECG features showed real promise when classifying between the two classes.

4. Conclusions

It can be concluded that S-ECG is able to detect AMI. The machine learning results are good, and the data analysis done for the features confirms the reasons behind why the models work.

The HF-ECG can also be proclaimed to be a relevant method for AMI detection. The features it can provide, give us more insight into the myocardial status of the patient, on top of the normal ECG.

It can also be concluded that a wearable device can be used for AMI detection. The possibility to measure ECG at home regularly and precisely, could turn out to be highly beneficial in the fight against AMI. It is reasonable to notice that none of the patients measured with the SAFE device were suffering from the disease that was studied. However, it is equally as difficult to predict the persons to be healthy and the quality of the ECGs gathered with the device was acceptable.

Future work would include increasing the dataset size and possibly measuring AMI patients with the device itself.

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