A Smartphone-only Solution for Detecting Indications of Acute Myocardial Infarction

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Abstract— **In this paper we consider the detection of indications of acute myocardial infarction (AMI) through a smartphone only solution. AMI is a serious heart condition where a blood vessel of the heart is fully or partially blocked e.g. by a rupture of an atherosclerotic plaque, the arrival of oxygen to the heart muscle is disturbed, and part of the heart muscle tissue dies (irreversible injury) due to insufficient oxygen supply. When a person feels obscure acute chest pain (angina pectoris), it may be caused, for instance, by heartburn or it may be a symptom of AMI. The goal of this paper is to develop a solution, which could either be integrated into an emergency App for the use of telemedicine by trained medical personnel or as a standalone solution to smartphone users in order to help recognizing this life-threatening condition earlier. The developed solution extracts the heart signal of a patient who lies in supine position by utilizing the built-in accelerometer and gyroscope within a smart device (e.g. a smartphone), which is placed on the chest of the patient. The solution does not require any external sensors for the smartphone to operate, but in the future it could be supplemented with ECG, for instance, to improve its performance. We have collected data with smartphone running Google Android from 17 AMI patients before and after percutaneous coronary intervention (PCI), and in addition, control recordings were performed in 23 healthy individuals (CG) and in 12 patients with stable coronary artery disease (CAD) before elective PCI.**

I. INTRODUCTION

Cardiovascular diseases (CVD) are a leading cause of deaths globally, up to 31.5% of all deaths of 54.9 million reported in the year 2013 [1]. Ischemic heart disease and stroke were among the most common causes of death among CVD at 2013. Especially in developed countries, the CVD are the leading causes of mortality. In the case such as acute ischemic stroke it is essential to seek into hospital emergency as early as possible. A coronary angioplasty operation can be used to remove the blockage from coronary arteries to reduce the damages caused by the loss of oxygen into the heart. A common symptom of AMI is acute chest pain, which can be also caused by other less severe phenomena such as heartburn. The time spent from the starting of the symptoms to the cardiovascular operation affects dramatically to the outcome of the treatment. Thus, it is essential to guide a person suffering from AMI symptoms and in need of medical treatment into the hospital as early as possible.

In ischemia there are two types of acute cardiovascular events, which can be classified according to the presence of the ST segment elevation in ECG. If coronary arteries are fully blocked, the height of the observed elevation is directly related to the severity of permanent damage to the heart muscle. This type of heart attack is called STEMI (ST-elevation myocardial infarction). For patients with suspected acute myocardial infarction, but without ST-segment elevation in ECG (only partially blocked coronary arteries), the ECG findings are unspecific and investigation of cardiac markers (e.g. troponin) is required to confirm the diagnosis [2]. In some cases a person might be unaware of the condition (NSTEMI, Non-ST elevation myocardial infarction), and it only manifest when the person is under exercise. In this paper we focus mainly on the detection of STEMI. Of the 8.6 million myocardial infarctions reported in 2013 approximately 3 million were ST elevation MI and more than 4 million NSTEMI. The purpose of this paper is to study possibilities to recognize AMI through cardiac motion sensors available in current standard smartphones.

II. BACKGROUND

Seismocardiography and ballistocardiography are well known methods to measure the heart's mechanical activity [3]. Seismocardiography uses accelerometers for this purpose and ballistocardiography, on the other hand, measures the pressure changes induced by the heart movement with special devices installed to the devices where the subject is on [3]. As an additional cue to seismocardiography/ballistocardiography, we utilize the also the gyroscope sensor within smartphone IMU (Inertial Measurement Unit) to observe the rotational vibration movement of the heart [7]. With 3-accelerometer and 3-gyroscope axes there are a total number six data channels for the data. Seismocardiography has been previously used to examine the changes induced by myocardial ischemia in several studies, see e.g. [4] [5] [6]. Using a smartphone to the analysis of the heart signals through seismocardiography is a relatively new topic, and to our knowledge it has not been applied to the detection of STEMI before.

III. PATIENT PROTOCOL AND DATA ACQUISITION

The data collected in this study consists of three sets of recordings. The first set consists of a total of 34 data recordings, of which 17 were captured from STEMI patients before before percutaneous coronary intervention (PCI) (we

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denote this set as STEMI) and 17 from the same persons after the intervention (STEMI-POST). The second data set consists of a control group of 12 CAD patients before non-acute elective PCI operation and the third data set of a control group of 23 healthy volunteers (CG). The first and the second data sets were captured at a hospital at Turku University Hospital, Finland, and the duration of a single measurement was typically up to a few minutes. The third data set of a control group of 23 healthy individuals was acquired at the the premises of Technology Research Center, University of Turku, Finland (with the same smartphone). In both cases, the subjects were adviced to lie in supine position, while a smartphone measurement was taken by setting a smartphone on the chest of the patients (screen upwards and loudspeaker towards the head). A dedicated data collection App built for a standard smartphone running Google Android OS and it was used to acquire the data upon pressing a button for starting and ending the acquisition. The research protocol was approved by Ethical Committee of the Hospital District of the South-Western Finland.

The requirements for inclusion of a patient for the study were:

- The age of at least 18 years old (a man or a woman),
- The patient was an authorized representative of himself (or herself) and willing to agree and sign a written informed concent related to the parcipation for the study, approved by the ethical review board,
- The patient was diagnosed MI/AMI/CAD by other standard modalities.

The criterias for exclusion of the patient from the study were:

- the patient suffered from any additional health problem that would, in view of the investigators opinion, interfere the patients optimal participation to the study,
- age under 18 years old,
- unwillingness or unability to use a smartphone
- the patient suffered from severe memory problems

We did not store any information which could be used to identify the patient into the memory of the smartphone, thus the patients were anonymized during the analysis of the data recordings. After the gathering of the data, the data was transferred to a desktop personal computer and Matlab, which was used to the development and validation of the algorithms. Due to the short duration of the measurements, the discomfort or possible disadvantages to the patients were minimized. The acquisition of the data nor the results of the off-line analysis had no effects to the threatment of the patient.

IV. SIGNAL PROCESSING AND FEATURE EXTRACTION PIPELINE

A. Pre-processing and artifact removal

The signal processing pipeline starts with filtering each of the six data channels separately by a bandpass brick-wall filter with pass-band frequencies between 1 Hz and 45 Hz. The purpose of this step is to remove the noise, bias of the signal and to emphasize the actual cardiac vibration signal. The sampling rate of the accelerometer and gyroscope within IMU was 200 Hz $\pm$ 3 Hz. It is challenging to get rid of this small variation in sampling rate when using smartphones for acquiring the data. The unstable sampling rate introduces errors when the data is processed and analysed. Therefore, the varying sampling rate and the different base sampling frequency in the smartphones need to be considered, when performing measurements based on IMU. We plan to study these issues more indepth in the future.

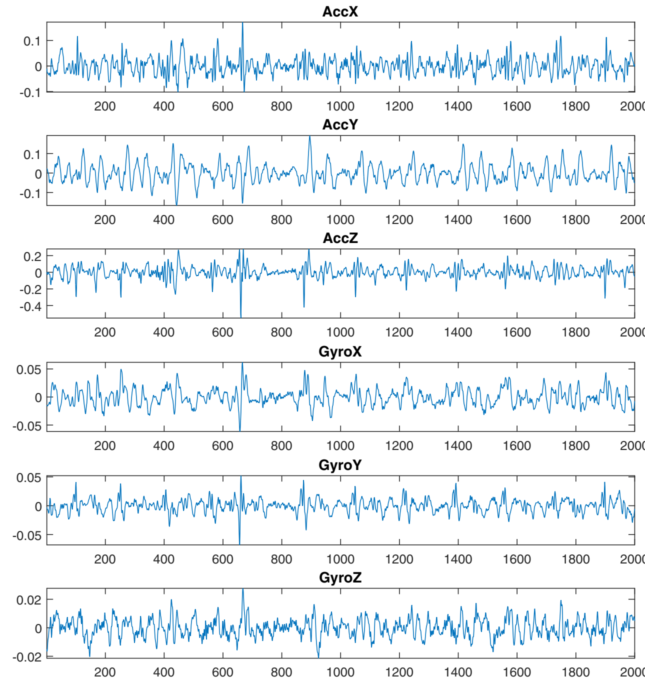

Fig. 1. 6-axis IMU recording of a person suffering from STEMI. Each axis was pre-processed with bandpass filtering and noise removal.

The motion artifact removal filter used in this study works as follows. First, a sliding window RMS (root mean square) filter is applied to capture the envelope of the data. If the RMS filter exceeds the median value of the whole signal (in ACC-Z axis) by an empirical threshold, the corresponding section of the signal is declared as an artifact and it is removed from all axes. The ACC-Z channel is parallel to the force of gravity when a person is in supine position. As a result, also after the noise removal the the temporal locations of the different data channels correspond to each other. When the noise removal has been completed using patient specific noise removal threshold for each patient separately, a further processing divides the artifact free signals into constant length (of 10 s) segments of 6-channels for the feature extraction purposes.

B. Feature extraction

Fig 1 shows an example of the 6-axis waveforms obtained from a person with diagnosed STEMI. We use 1-D local binary pattern (LBP) features for the detection of STEMI [8]. Also several other different features were tested, such as

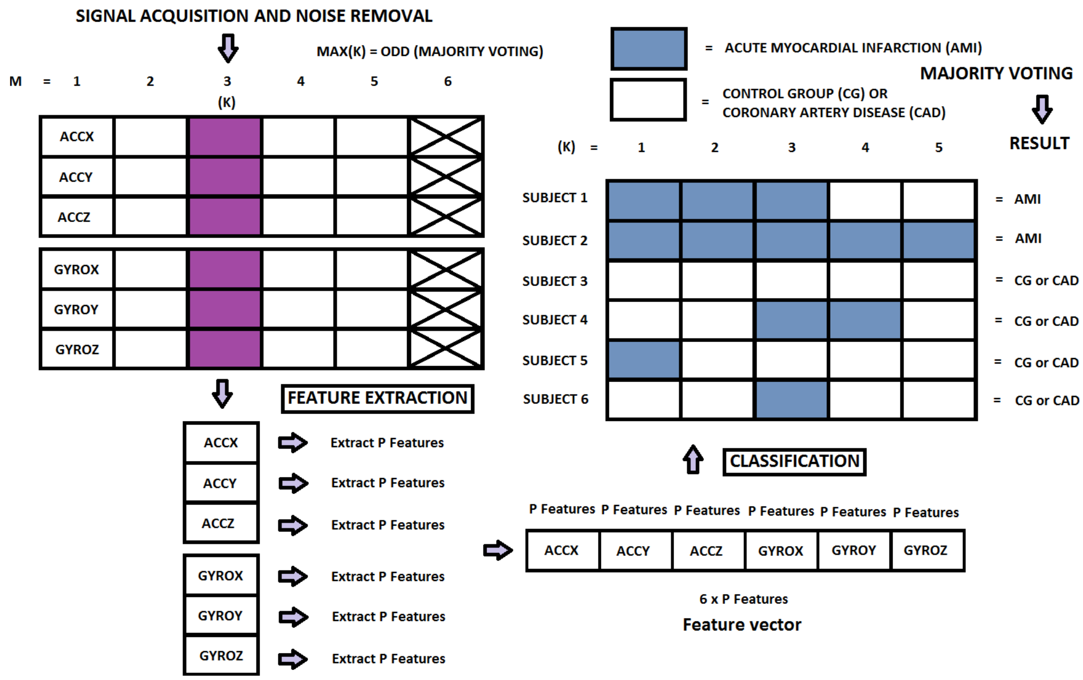

Fig. 2. Overall diagram of the machine learning part of the STEMI detection (two-class case). A feature vector includes one LBP histogram with fine spacing (r=3) of the original signal (after filtering and noise removal) and one LBP histogram for an integrated version of the same signal (with Matlab *cumtrapz* function) with fine spacing. Additionally, the same procedure is applied to signal with a coarse spacing (r=21). In total there are four LBP histograms of length 59 bins corresponding to single segment and axis (P=4*59). The length of the overall histogram for six axes is 6*P features.

heart rate and heart rate variability, but of these the LBP gave the best performance. The origin of LBP methodology lies in texture image analysis, but it has since found to be applicable for various other image processing tasks, such as face recognition and other biometrics and beyond (see [9] [10]). LBP is invariant to signal bias, which is believed to make it suitable for the analysis of the actual shape of the underlying signal and its small scale micro-structure. Here, we use four LBP histograms to describe the structure of the heart signal segment (of length 10 s) specific to a certain axis. Two histograms include small-scale temporal signal variation and larger-scale temporal signal variation. The small-scale variation is derived by calculating a $LBP(M = 8, r = 3)$ histogram and the larger-scale varation is calculater with $LBP(M = 8, r = 21)$ histogram, where M is the number of bits in the LBP and r is the spacing between successive LBP bits temporally.

The motivation of using two different spacings is that the smaller spacing is assumed to cover the intra-beat shape of the signal within a single axis, while the larger spacing also contributes to the signature of the inter-beat shape within the signal. The two LBP histograms are calculated for both the original signal (which has been filtered and from which noise have been removed) and to its integrated version (integrated with Matlab's *cumtrapz* function). The motivation for using integrated signal also is to measure the cumulative deviation of the signal segment, which could be different between a healthy and a diseased heart. The 1-D LBP, and LBP in general is derived so that the center sample within a window is compared to its neighboring samples. In the case of 1-D LBP, a center sample is chosen one at a time for the full signal length (omitting border samples in the beginning and in the end of the signal) and the signal values at time instants before and after the center sample (within a window defined by the M and r) are compared to each other. If the center sample is smaller than the neighboring sample a bit 1 is assigned (bit 0 otherwise) into the LBP binary string. The number of occurrences of each of the strings, which have been converted into a decimal is calculated. The final feature vector consist of a histogram of these bins. Usually, only bit-strings with 2 or less bitwise circular changes are selected in the end, since these so called uniform patterns are the most discriminative and dominant patterns [10].

V. EXPERIMENTAL METHODS AND RESULTS

A. *Classification and Cross-validation*

For classification we tested Support Vector Machine (SVM), Kernel SVM (KSVM) and Random Forest (RF, bagging) classifiers. We used leave-one-person-out (LOOCV) cross validation to evaluate the sensitivity and specificity of classification algorithms. This means that one person at a time is left out from the training set, so that the training set contains no data specific to the individual which is being tested. This is possible, since each data segment is associated with a label corresponding to an individual. Majority voting selects the most common class for each person, which is the final recognition result. In this paper we report the results from the best performing classifier (KSVM). Fig. 2 shows a diagram of the two-class classification pipiline.

B. Classification results

The confusion matrices are reported without majority voting (a) and with majority voting (b). For the STEMI vs. CG the confusion matrix is (a) [**92** 16; 16 **282**] with a sensitivity of 85.2% of and a specificity of 94.6% (b) [**14** 3; 1 **22**] with sensitivity of 82.4% and specificity of 95.7%. For STEMI vs. CAD case the results were (a) [**67** 41; 52 **72**] with a sensitivity of 62.0% and a specificity of 58.1% and (b) [**14** 3; 4 **8**] with a sensitivity of 82.4% and a specificity of 66.7%. KSVM with LOOCV was used in all of these experiments. STEMI detection performance between states STEMI vs. STEMI-POST was (a) [**81** 27; 14 **90**] with a sensitivity of 75.0% and a specificity of 86.5% and (b) [**11** 6; 3 **14**] with a sensitivity of 64.7% and a specificity of 82.4%. In the case of STEMI vs. STEMI-POST the majority voting did not improve the performance.

VI. DISCUSSION

In general, an AMI detection App (or equivalent such as in [11]) has accomplished its mission if it is able to guide the patient at an acute situation to seek for care more rapidly. In the contrast however, if an App causes a delay for a person in need of medical care, who trusts enough that App is reliable, in seeking for advice, for instance due to classifying a sick person as healthy, the Apps mission has failed. These serious ethical issues should be carefully considered before releasing any solution to public. In the case of personal healtcare App, the patient should be adviced to follow the common standard procedures in seeking for medical care, but potentially accelerating the time-to-treatment when the symptoms onset. The final diagnosis of the situation will always be made by emergency staff on-site or in the hospital with the available sensing modalities such as ECG and blood markers.

In this paper the acquired data, especially STEMI data, was relatively noisy, but in the future the results might be improved by collecting more data and by the development of better noise cancellation methods. In the future, it would also be beneficial to include a synchronized ECG or PPG (photoplethysmography) to the IMU data, as in our case only IMU data was acquired. Utilizing both IMU and ECG might provide complementary cues to detect STEMI, in comparison to ECG-only or IMU-only case.

In addition to data acquired at a hospital, a personal App for the detection of AMI could acquire healthy intra-personal data from the subject before any symptoms or indications of AMI. It would be beneficial, if the machine learning algorithm could then benefit from this single-class data as well, where the intra-personal STEMI data might not yet exist. In this paper we did not include any data of the person under test to the training set, thus utilizing the intrapersonal healthy-class data might improve the classification performance in the future. Occasionally a blockage in the blood vessel of the heart develops slowly without notable symptoms at the beginning, except potentially during hard physical exercise. It would be beneficial if indications of that kind of situation (NSTEMI) could be observed before the actual full blockage of the blood vessel.

VII. CONCLUSIONS

We have developed methods to find indications of STEMI through a smartphone-only solution. The envisioned App could be operated through telemedicine solution at distant emergency center or as a stand-alone solution to the smartphone App users. However, before releasing any App to actual use or public distribution, the ethical issues will need to be covered as well as clinically validate the algorithms with more extensive statistical tests and data collection. We believe that through collecting more data, by the development of more advanced noise cancellation and noise detection, as well as by the development of more sophisticated feature extraction methods could even further improve the detection rates of this paper. In the future we plan to perform experiments based on multimodal synchronously collected data with concurrent ECG and IMU modalities, as well as to extend the study to cover also other heart abnormalities such as NSTEMI.

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