# Heartbeat Tracking Application for Mobile Devices - Arrhythmia Recognition Module

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**Abstract.** *We want to introduce a lightweight system for arrhythmia recognition. The system is intended for outdoor use and is supposed to be implemented in mobile devices, primarily smart phones and smartwatches. We are only concerned about extracting pulses from an ECG stream and passing them to an Arrhythmia Recognition Module - ARM. These two basic tasks should be completed fast and effectively and give an alert when arrhythmia occurs. The ARM we designed relies on simple algorithm for feature extraction and gives an error of 2.007% with false/positives over false/negatives ratio of 19.*

**Keywords.** arrhythmia recognition, pulse extraction, feature extraction, support vector machine, mobile application

## 1. Introduction

Arrhythmia is something that may happen to people that go outside urban areas for physical activity and usually put their body in extreme physical condition, leading to fatal outcome in number of cases.

We can target several groups of people that should benefit from having their heart behavior monitored and be alerted when something goes wrong. Outdoor sports like cycling, hiking, walking and cross-country running are amongst the most recommended sports for maintaining good cardiovascular condition. On the other hand, there are numerous extreme sportsmen that put their bodies to the limit under extreme conditions: high humidity, low oxygen level, very high or freezing temperatures and stress. There is a third group of people that have some calculated risk of arrhythmia when exposing their body to super-optimal effort like: people who have hypertonia, people that suffered heart attack, brain attack or brain bleed, diabetes patients and people who suffer from problems with heart electrical conductivity [1, 5]. Another group of people are those in their 50's and above which are getting more involved in sport activity in the past years, and they are more prone to arrhythmia under continuous physical effort.

Tracking vital functions and getting a response from a system can help people stabilize their organism, make some precautions when unexpected behavior arises or take some necessary actions while waiting for medical help [7, 8]. The system we propose is based on detecting arrhythmia. We are not interested in the type of the arrhythmia - we only want to raise an alert signal when something is wrong with the hart rhythm and behavior. This system does not make diagnosis for the user's condition, but provides first aid assistance while waiting for medical help. It is not meant to trigger a whole system, like calling an ambulance, upon raising an arrhythmia



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signal. However, there is an option for calling an ambulance.

It is our great concern for this system to work with satisfactory reliability, with low resource consumption, so that other applications, that are commonly used while performing this kind of activity, could work in parallel: Internet radio, MP3 players, GPS navigation or other applications, or a combination of them [14].

In Section 2 we give a definition of the problem, in Section 3 we describe the system with its modules. In Section 4 we elaborate the results for the recognition performance of the ARM. The further research is described in Section 5 and finally in Section 6 we give a conclusion for this paper.

## 2. Definition of the problem

This system, shown in Fig 1., should raise an alert signal when arrhythmia is detected in the ECG of people that are exposed to physical effort, mainly outside urban areas. Sensing only vital signals is sometimes not enough for efficient evaluation for heart malfunctioning existence. This system is not designed to make diagnosis of the condition of the user - this is something only a physician can do. It only gives description of the health condition in the moment and some instructions based on the sensors' input and question/answer interaction. That way the user or another person can know how to act to stop further deterioration of the user's condition, try to partly stabilize it or eventually give first aid right at the spot, while waiting for the ambulance.

There are a lot of types of arrhythmia and some are harder to recognize than the others [6]. The system should be reliable enough to overcome this problem [3]. Additional vital signs, like blood pressure and oxygen saturation, are essential to make decision logic work reliably [7].

## 3. System description

The system is comprised of ECG transmitter, vital signals sensors and Mobile ECG Application. The mobile application has two main modules: the ECG Processing Module - ECGPM and the Mobile Physician Module - MPM. The ECGPM consists of two parts: Pulse Extractor and Arrhythmia Recognition. The MPM is a mobile application and is intended to be installed on smartphones, but not on smartwatches . Smartwatches only raise alert signal and display a short text message, because of their very limited resources. The signal comes from the ECG transmitter and is then passed trough ECGPM, where pulses are extracted and tested against trained arrhythmia recognition machine. If an arrhythmia is recognized, an alert signal is raised and MPM is launched. Along with the data from the vital signals sensors and trough interaction with MPM the user gets valuable information of how to engage the heartbeat disorder.

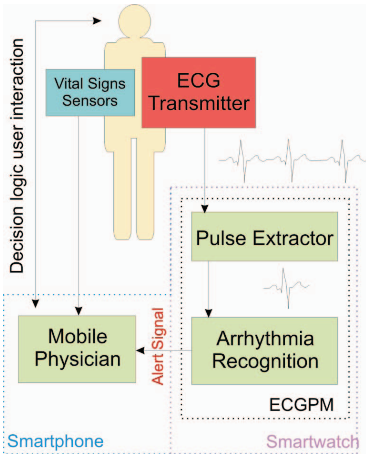


**Figure 1. An overall look of the system**

### 3.1 Pulse Extractor

Numerous QRS detection algorithms such as derivative based algorithms, algorithms based on digital filters, wavelet transform, length and energy transform, artificial neural networks, genetic algorithm, syntactic methods, Hilbert transform etc. are reported in literature [10, 11 , 12]. They are all based on QRS complex detectors. Detecting P and T waves and the ST complex, which form a regular and complete cardiac period is performed relative to the QRS complex. Most of these pulse detection algorithms have m-class classification problem in mind. The algorithm we propose has completely different approach – we don't detect QRS complex, but a separation line between pulses and we are interested only in 2-class classification.

The Pulse Extractor – PE extracts the pulses from the ECG stream. In our approach a pulse is considered to be everything that is in between two straight lines or slopes. The algorithm from the PE works only with ECG streams that adhere to the previous condition. This is sufficient for the algorithm to perform well because regular pulses are always separated by straight lines or slopes. Since the pulse is handed to the Arrhythmia Recognition module which decides weather there is arrhythmia or not, each pulse that is not regular according to the PE is considered to be a potential arrhythmia. As we know, arrhythmia has repetitive behavior, so we raise the alert signal when we detect not only one isolated irregular pulse, but when those pulses occur in a certain time slot. If the type of the arrhythmia is of the kind that separation lines are very hard to detect, the extracted pulses will be very long and most certainly irregular, so the alert signal will be raised. This approach of the algorithm is justified by the fact that we are only interested to detect irregularity in the heart activity. Another thread of the algorithm is dedicated to measure the distance between the R points of the regular ECG. Significant difference between consecutive regular pulses also signals arrhythmia.

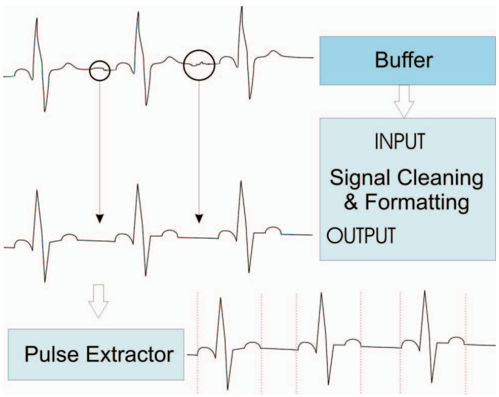


**Figure 2. Stream preparation for pulse extraction**

Another part of the algorithm, that is still not fully implemented and tested, is the "cleaning" of the ECG stream. It is a fact that we can eliminate the noise from the ECG signal up to a scale, but the signal is not ideal – we can not recognize ideal curves or lines and this may corrupt the extraction. Therefore an intermediate level of "cleaning" the signal is needed for the above PE algorithm to work. In Fig 2. we can see that cleaning the "signal" means that the signal is transformed into ideal curves and lines. After that we can precisely extract the pulses from the ECG stream according to the paradigm described in the beginning of this Section. We use the "cleaned" signal only to evaluate the pulse length, its beginning and end in the stream. Once we do that we come back to the original signal, extract the pulse from there and pass it to the Arrhythmia Recognition Module.

### 3.2 Arrhythmia Recognition Module

Machine learning is commonly used technique for ECG diagnosis. Several main techniques are used: Support Vector Machines, Fuzzy Set Theory, Neural Networks, Rough Set Theory, Hidden Markov Model and Hybrid Approaches giving accuracy between 70% and 100% [13]. Each of them has a number of different methods for feature extraction. We use SVM for recognition of the samples, which by Salem [13] have accuracy span of 88% - 100%.

The recent results in pattern recognition have shown that support vector machine (SVM) classifiers often have superior recognition rates in comparison to other classification methods. Because of this, we decide to use this classification technique for solving the arrhythmia recognition problem. Additionally, the features obtained by the feature extraction method explained in the following paragraphs, are not human interpretable and we are not interested in knowledge discovery techniques. The time and computational complexity of SVM is not high, because of the small length of the feature vectors.

The arrhythmia recognition module is the heart of the entire system [7, 12]. Therefore, we have to make sure it performs well and gives satisfactory results. We used the MIT-BIH Arrhythmia Database to extract the regular pulses and arrhythmia pulses. The ECG recordings in the database are represented by samples (discrete values) taken every 0.0028 seconds and we worked with the first 60000 samples from a recording. Pulses, being either regular or irregular (arrhythmia), consist of number of samples ranging from 200 to 500 samples per pulse. We included 16 different patients (recordings) in the process of obtaining pulses. We used 8 of them for obtaining arrhythmia pulses, and 8 of them for obtaining regular pulses. The pulse extraction was performed automatically with a light version of the PE algorithm (without ECG cleaning and formatting) and some manual calibrations of the parameters of the algorithm. This algorithm basically finds a piece of the stream with defined length, where each of the slopes between points at a certain distance is in predefined bounds. This way we detect the separation of the pulses. Afterwards we detect the closest slope above some value on the left and on the right of the separation line. The left point marks the end of the previous pulse, and the right one the beginning of the next pulse as shown in Fig. 3.

The pulse sample database we built from the 16 different patient ECG recordings has 1064 pulses in total, 548 of which are regular and 516 irregular i.e. arrhythmia. The pulses have been already noted with a mark for regular pulse or the type of the arrhythmia. Several types of arrhythmia, but not all possible, were included in the training and testing of the SVM: paced beat, right bundle branch block beat, premature ventricular contraction, fusion of ventricular and normal beat, left bundle branch block beat and atria fibrillation. When making a two class classification, the statement: if an object does not belong to class A, it must belong to class B is what defines the core of the problem.

When extracting regular pulses we must make scaling of the both X (Fig. 4) and Y axis. Scaling of the Y axis eliminates the vertical offset of the pulse (people do not have same potential when heart is in relaxed mode). This will eliminate the false features that may occur because of that offset: we are interested in the pattern of the regular pulse, not the offset. Arrhythmias can be scaled only by the X axis. Since we do not make classification of the arrhythmias by their type, the difference in the offset is not important.

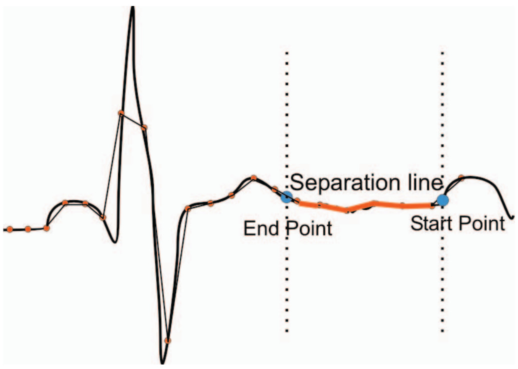


**Figure 3. Finding the separation line, the end point and the start point**

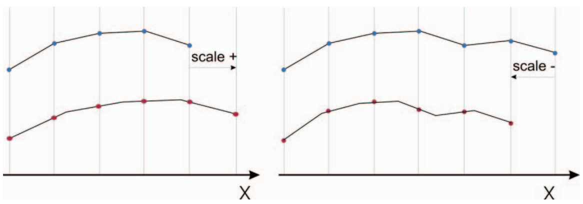


**Figure 4. Scaling of the pulses**

After the scaling of the pulses to a referent width i.e. number of discrete values that represent the pulse, we perform normalization of those values. Each pulse is represented by 300 discrete values. If we consider those values to be dimensions, we say that we normalize the pulses by their dimensions.

$$x_{ij,normalized} = \frac{x_{ij} - \overline{x_i}}{\operatorname{var}(x_i)}$$

where $x_i$ is the $i$-th dimension of the pulse and $j$ is the pulse number. After the normalization we select the features by averaging certain number of dimensions of a pulse. We have 30, 20, 15 and 10 feature vectors. For example for the 30 features vector we average the values of every 10 dimensions of a pulse, for the 20 feature presentation – values of every 15 dimensions and so on. The results from the tests are described in detail in Section 4.

### 3.3 Mobile Physician

The Mobile Physician - MP is intended to be the system's interface to the user and to suggest steps that user should follow until medical help arrives. Isolated ECG signal does not provide enough symptoms to precisely detect the syndrome, so there are additional input vital signals to the MP: blood pressure and oxygen saturation. Trough a series of questions and answers, the user is guided to perform some actions that will most probably stabilize his/her condition or will just give the user instructions how to remain calm while help arrives in case of more severe disorder. For instance, alarm can be raised for a person that suffers arrhythmia from two reasons: entering an arrhythmia cycle or having a heart attack. The MP can tell the user he/she is entering an arrhythmia cycle and suggest to take a pill and call the ambulance, or say that he/she is having a heart attack and should take nitroglycerin if available and call the ambulance. This is especially important when the user finds him/herself outside urban area. In some cases the MP can provide steps for first aid to a second person that is accompanying the user or is just passing by. It is important to note that MP does not make any diagnosis on the spot – it only acts as a guide to provide first aid or steps to follow until medical help arrives or while the user is transported to a medical facility. Another important thing is that there is an emergency button that appears in the MP. By pressing it the user calls the ambulance.

## 4. Test results

Training and testing of the support vector machine (SVM) in the ARM module was performed using a custom developed application that uses the Torch library [4]. For solving the binary classification problem SVM using Gaussian Kernel was used. From our past experience with SVM, Gaussian Kernel has shown to give best results.

All tests were performed on personal computer with Genuine Intel CPU T2050 processor, in Centrino Duo technology, at 1.60 GHz on 32-bit operating system Windows Vista.

The classification accuracy is determined using five cross-validations over the set of 1064 samples from the 16 patient records. In Table 1 we see the distribution of records over the folds and regular and arrhythmia pulses over the training and test sets. The records marked from 1 to 8 correspond to 8 patients with regular pulses, and records marked from 9 to 16 – to 8 patients with arrhythmia pulses. We choose the arrhythmia pulses to be positive outcomes, and the regular pulses, negative outcomes in the classification.

**Table 1. Pulse distribution table: A - total number of arrhythmia pulses; R – total number of regular pulses; (Tr | Te) / (A | R) : type of set / type of pulse**

| Fold | Training Set | Test Set |
|---|---|---|
| A | 1,2,3,4,5,6,9,10,11,12,13,14 | 7,8,15,16 |
| B | 1,2,4,5,6,8,9,10,11,12,13,15 | 3,7,14,16 |
| C | 1,2,4,6,7,8,9,10,11,12,13,15 | 3,5,14,16 |
| D | 1,2,4,5,6,7,9,10,11,14,15,16 | 3,8,12,13 |
| E | 1,2,4,5,6,9,10,11,14,15,16 | 3,7,8,12,13 |

| Fold | A | R | Tr/A | Tr/R | Te/A | Te/R |
|---|---|---|---|---|---|---|
| A | 516 | 548 | 400 | 411 | 116 | 137 |
| B | 516 | 548 | 415 | 425 | 101 | 123 |
| C | 516 | 548 | 415 | 458 | 101 | 90 |
| D | 516 | 548 | 453 | 436 | 63 | 112 |
| E | 516 | 548 | 453 | 362 | 63 | 186 |

We made a series of test for each fold to obtain the minimum error rate by changing the Kernel parameter σ (standard deviation) from $10^{-1}$ to $10^3$ and setting the SVM parameter $C$ (error penalty) to 100. Table 2 shows the best results obtained for each feature vector selection.

As we can see from Table 2, we get the best results from the 10 feature vector. As we increase the number of the features we get bigger error, because of over-fitting the SVM - more information to the SVM makes it more difficult to set the decision plane. For the 10 feature vector and repeat the experiment, we get an average minimum error of 2.007%. The average of falsely recognized samples is 4, but what is more important is that we get an average of 3.8 false/positives against 0.2 false/negatives. This is very important because it means that if an error occurs, it is a small probability it would be an unrecognized arrhythmia.

**Table 2. Recognition results: σ – standard deviation in the Gaussian Kernel function; F – false classifications; F/P – false positives; F/N – false negatives; Error % - percent of false classifications**

| Features | σ | F | F/N | F/P | Error (%) |
|---|---|---|---|---|---|
| 30 | 2 | 8 | 4,8 | 3,2 | 3,772 |
| 20 | 12 | 8 | 4,8 | 3,2 | 3,742 |
| 15 | 10 | 6,4 | 3,8 | 2,6 | 3,020 |
| 10 | 9 | 4 | 0,2 | 3,8 | 2,007 |

## 5. Further research

The further research will be mainly focused on full implementation and estimating the speed of the Pulse Extractor - PE algorithm, speeding it up and getting better performance. We will also have to examine the effect of users' motion: walking and running; on the performance of the PE algorithm. Utilization of various mobile device resources should also be well examined [14].

Another very important issue to improve is the Mobile Physician into a more reliable assistant. The general idea of the upgraded system is depicted in Fig 5. In future, we would also like to consider the environmental input (from sensors): altitude, humidity and temperature; location (from GPS) [2]: state park, forest, mountain, desert, riverfront, lakeshore; and clothing (interaction with the user).

This system is prospective to become a part of a much larger one that will include a reference to the patient EMR. Referencing the EMR is a very important part of the decision logic and may significantly improve its reliability. Streaming the data from the sensors along with a video to a physician can replace the MP. This way the user will be "guided" by an expert when in critical condition, but only if Internet connection is available. MP would still remain an important part in the system.

It will be very useful to record ECG and vital signals during the physical activity, along with the input from the environmental sensors. This log will be very useful when a physician tries to diagnose the cause for the arrhythmia.

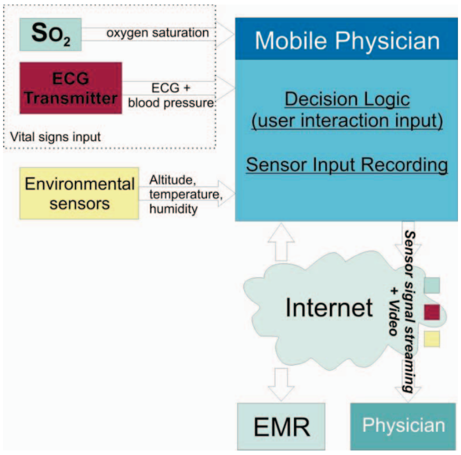


**Figure 5. An idea for the system in the future**

## 6. Conclusion

This system detects malfunctioning of the heart and alerts the user. It is supposed to recognize any kind of arrhythmia, but not the type. The system gives instruction to the user to temporarily engage the situation until medical help arrives. This kind of on-time first aid may save numbers of lives and make people more confident when going outdoors for sport activities, extreme sports, professional sport practice or for maintaining physical condition after suffering some health problems.

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