The Comparison of Algorithms for Life-threatening Cardiac Arrhythmias Recognition

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Keywords: Electrocardiogram, Arrhythmia, Spectrum, Classification, Fourier Transform.

Abstract: During the clinical monitoring of the human heart activity the main goal is to detect heart arrhythmias and capture their precursors as early as possible. And we decided to apply 2 seconds gliding window for life-threatening cardiac arrhythmias recognition. All types of arrhythmias were grouped into six classes depending on their danger to the human life. And these classes were separated in two parts: threatening humans' life and others. As a classification features Fourier transform with spectrum up to 15 Hz were picked. In this paper we describe the formed dataset of ECG fragments and compare efficiency of different simple classification algorithms for this two-class problem. The following algorithms were tested: k-nearest neighbours, nearest convex hull algorithm, nearest mean and SVMs with different kernels. The results appeared to be sufficiently appropriate.

1 INTRODUCTION

Perspective intelligent outpatient monitoring systems aim not only at long-term electrocardiogram monitoring by also providing doctors and patients with alarms based on the results of its online analysis. Prominent applications of such systems include detection of various life-threatening disorders such as severe arrhythmia and/or ischaemia events as well as signatures of such conditions as stroke and cardiac arrest. Such as ventricular fibrillation (flutter) and tachycardia in 40% of cases lead to cardiac arrest (Wik et al., 2003). Electric defibrillation is only effective therapy for these disorders. For the successful implementation of life-threatening cardiac arrhythmias recognition algorithms and their online performance, the keynote requirements include reliability and detection time (Moraes et al., 2002; Meng et al., 2016). A large number of algorithms have already been developed and tested using various classifiers and features to solve this problem. In (Xu et al., 2018), authors have made a review and comparison of these algorithms and methods proposed in the last decades.

Different features of life-threatening cardiac arrhythmias (Cheng and Dong, 2017) were proposed for the algorithms of their detection: morphology analysis (Arafat et al., 2011; Amann et al., 2006; Monte et al., 2011), spectral analysis (Barro et al., 1989; Dzwonczyk et al., 1990), time-frequency analysis (Millet-Roig et al., 1999), complexity measure (Zhang et al., 1999; Roopaei et al., 2010), wavelet analysis (Rasooli et al., 2015; Balasundaram et al., 2013; Li et al., 2011), empirical mode decomposition (EMD) (Arafat et al., 2009; Anas et al., 2011; Kaur and Singh, 2013), sequential detection methods (Anas et al., 2010; Thakor et al., 1990), machine learning (Verma and Dong, 2016). However, the authors used different databases and datasets for their methods testing. In (Amann et al., 2005) the majority of these methods were tested under the same conditions by using open published annotated databases, and it was shown that they could not achieve the proclaimed performance.

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Nemirko, A., Manilo, L., Alekseev, B., Sokolova, A. and Yuldashev, Z.
The Comparison of Algorithms for Life-threatening Cardiac Arrhythmias Recognition.
DOI: 10.5220/0009374904020407
In *Proceedings of the 13th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2020) - Volume 1: BIODEVICES*, pages 402-407
ISBN: 978-989-758-398-8; ISSN: 2184-4305

The current standard for clinical monitoring systems is to determine the onset of ventricular fibrillation in 5 seconds after the episode starting. However, when it comes to such a dangerous heart conditions, every second saved can have a huge impact on a patient's health and life.

Based on these statements, the following task was set: to reduce the detection time of the classification algorithm of dangerous arrhythmias and, additionally, to try to determine the occurrence of non-dangerous violations that are highly likely to evolve into dangerous ones. They are related to precursors.

2 DATABASE AND PPEPROCESSING

We used «The MIT-BIH Malignant Ventricular Ectopy Database» (Goldberger et al., 2000). It contains 22 two-channel annotated ECG recordings each of about 30 minutes duration, with a sampling frequency of 360 Hz. The recordings obtained from the patients who experienced various types of heart disorders: ventricular ectopic beats (bigeminy, trigeminy, couples and groups), atrial tachycardia, atrial fibrillation, pirouette tachycardia, ventricular tachycardia, ventricular flutter and ventricular fibrillation. For each of the signals, a set of annotations was manually verified according to time points of heart rhythm changing.

The recordings of this database were used as the initial data for the formation set of two-second segments in our own database. The process of this database creation is described below.

The signals represented in the original database are obtained using professional electrocardiographs and are almost free of power grid noise or high-frequency noises. However, there is still a noticeable baseline drift corrupting some parts of the signal (fig. 1 A).

Before creating our database of two-second fragments, the initial signals were processed using a median filter with a window of 1.3 seconds, which has removed the baseline drift. Remnants of electrical network interference and high-frequency noise (such as a myographic noise) with a frequency more than 50 Hz were removed using a high-order digital low-pass filter with a cutoff frequency of 45 Hz. Figure 1 shows a fragment of ECG recording, which contains the baseline drift and high-frequency interference (A) and after their reductions (B).

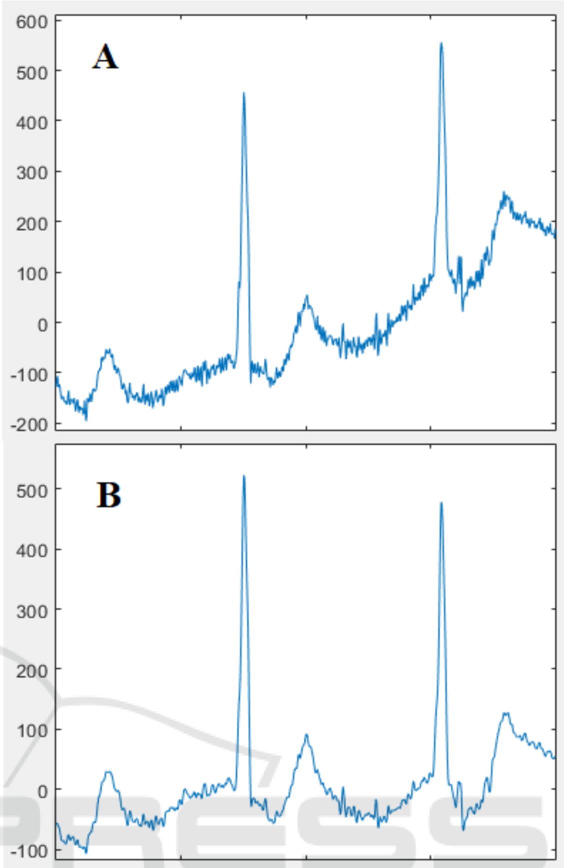

Figure 1: ECG fragment before preprocessing (A) and after (B).

3 NOVEL CLASSIFIER DATASET ACCORDING TO ARRHYTHMIA SEVERETY

The separation of ECG fragments into 6 classes was proposed. The base for novel classifier set was their potential danger to the life and health of the patient. Classes are listening according to the descending order of the danger:

- Class 1: ventricular flutter and ventricular fibrillation.
- Class 2: pirouette tachycardia.
- Class 3: ventricular tachycardia.
- Class 4: bigeminy, high degree of ventricular ectopic activity, ventricular rhythm.
- Class 5: atrial fibrillation, supraventricular disorders, nodular rhythm.
- Class 6: normal rhythm, single extrasystoles.

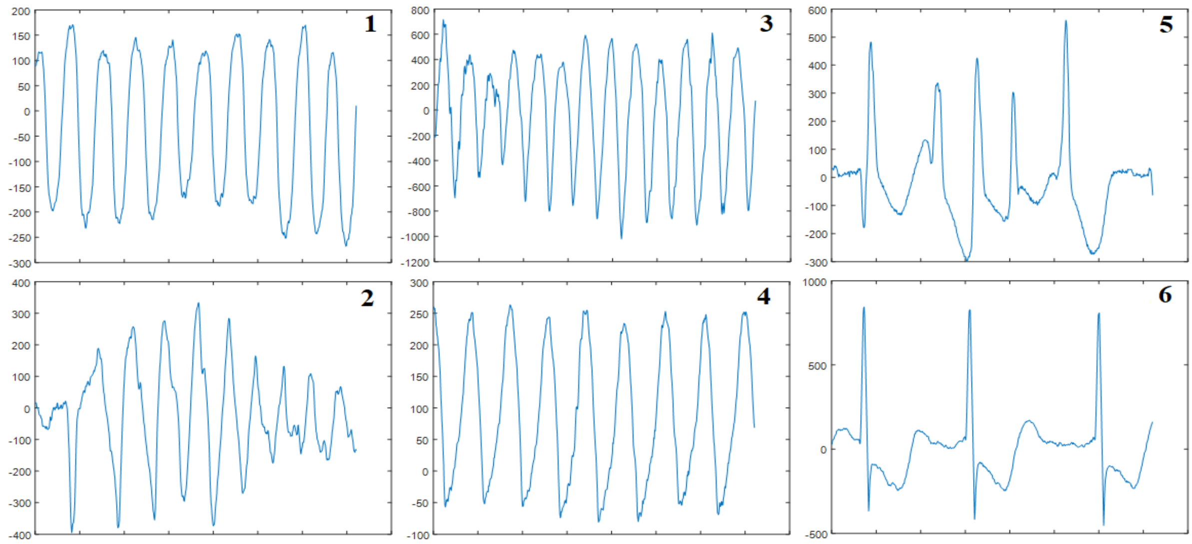

Figure 2: Examples of the representatives of each class.

Figure 2 shows typical ECG fragments for representation of each class.

The aim of this research was the detection of life-threatening arrhythmias in a much shorter time than common practices.

We used 2 seconds window to analyze ECG fragments for arrhythmias recognition. This window time duration allows investigating at least two QRS and RR interval between them for classes 4 and 6, and several waves for classes 1-3 and 5.

During the creation of new sets of two-second fragments from the original signals, 1000 fragments were cut, so that in each of the six previously designated classes there were at least 90 objects.

The table 1 presents number of two-second nonoverlapping fragments from the MIT-BIH database for each class.

Table 1: Number of analysed fragments.

Class	1	2	3	4	5	6
Quantity	220	113	183	90	133	261

Then we have consolidated above certain classes in two groups: life-threatening arrhythmias (Classes 1-3) and their precursors (Classes 4-6).

Thus, the testing of all considered algorithms was carried out on a two-class recognition – "life-threatening violations" and "others".

To truthfully check the quality of classification algorithms tested further, it was necessary to ensure an equal number of objects of each class in the training and test data sets. Thus, 90 fragments of six classes were included in the set, forming 2 enlarged groups of 270 objects.

The Fourier transform of the fragments was used as the features supplied to the classifiers. It was picked as a widely spread characteristics with high interpretability. Since the duration of the studied fragments is 2 seconds, the frequency step of the spectrum is 0.5 Hz.

At the initial stage of the work it was planned to use the union of harmonics in pairs to obtain a reduced spectrum with a step of 1 Hz, but the first results showed a significant decline in the accuracy of the algorithms when combining harmonics and as a result, 30 harmonics (up to 15 Hz) seemed to be the best in terms of information amount/computing difficulty ratio. Thus, they were used in the experiments.

4 APPLIMENTATION DIFFERENT ALGORITHMS TO ARRHYTHMIAS RECOGNITION AND RESULTS

4.1 Algorithms

Four classification algorithms were investigated in the study.

The K nearest neighbour classifier (kNN) is based on determining the most common class among the k nearest known objects to the one being classified. Testing different k's revealed k = 6 to be the best option.

Light nearest convex hull classifier (LNCH) represents classes in the form of convex hulls. The classification algorithm determines the position of the new object relative to these shells (Nalbantov and Smirnov, 2010; Nemirko, 2019). This method requires the biggest amount of computing among all tested ones, since it requires the calculation of a large number of projections of objects in n-dimensional space for each classified object.

As for the nearest mean method, the decision on whether an object belongs to a class is made on the basis of the euclidean distances from the object to the centres of the classes – their generalized objects.

Finally, the well-known method of support vectors with several variants of kernels was used in the study. Tested kernels are: linear, quadratic, cubic and Gaussian one.

4.2 Results and Discussion

To avoid overfitting of some algorithms, cross-validation was used during all tests.

Standard metrics of sensitivity (Se), specificity (Sp) and overall accuracy (OA) were used to determine the efficiency of the algorithms.

To test whether preprocessing has any impact on accuracy, additional tests using not-preprocessed data were conducted. The results are shown in the table 2. The best results are marked bold.

Table 2: Quality metrics of investigated algorithms applied to data without preprocessing.

Algorithm	Se	Sp	OA
kNN, k = 6	91,1%	96,7%	93,3%
LNCH	86,7%	91,1%	88,9%
Nearest mean	78,9%	93,3%	86,1%
Linear SVM	91,5%	94,4%	93,0%
Quadratic SVM	**95,9%**	93,7%	**94,8%**
Cubic SVM	**95,9%**	93,7%	**94,8%**
Gaussian SVM	94,8%	**94,4%**	94,6%

Based on the obtained kNN results, we can conclude the unequal dispersion of objects within the studied classes: the low sensitivity of the algorithm is explained by the presence of a large number of outliers in the class of "life-threatening arrhythmias". For the same reason the light nearest convex hull classifier shows poor results, as its's data quality requirements are the biggest.

Accuracy of the same algorithms after signal preprocessing are shown in the table 3.

It is interesting how the overall accuracy decreased after removing the zero drift from the signals. This is probably due to the much greater prevalence of zero drift precisely during occurrences of life-threatening arrhythmias.

Table 3: Quality metrics of investigated algorithms applied to data after preprocessing.

Algorithm	Se	Sp	OA
kNN, k = 6	89,6%	95,9%	92,8%
LNCH	85,6%	90,0%	88,8%
Nearest mean	78,5%	93,7%	86,1%
Linear SVM	91,1%	91,9%	91,5%
Quadratic SVM	95,6%	93,3%	94,4%
Cubic SVM	**95,9%**	93,7%	**94,8%**
Gaussian SVM	94,1%	**94,4%**	94,3%

After reviewing the objects that gave an error on most algorithms, 2 similar cases were identified that could not be correctly classified in the frequency domain. Examples of such fragments are shown in figure 3.

The first error source is significantly irregular ventricular fibrillation, giving a blurred spectrum similar to that of a normal ECG (figure 3A). The second case is transitions within the analysed

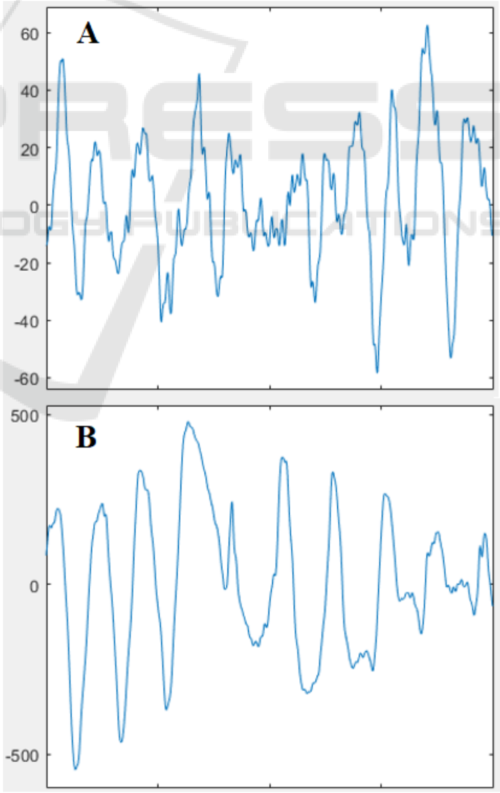

Figure 3: The examples of most common error sources: significantly irregular ventricular fibrillation (A) and transitions between different rhythm types (B).

segment. This situation is typical for episodes of the pirouette form of ventricular tachycardia, appearing for a very short period of time before the start of ventricular tachycardia itself (figure 3B). Both of these cases do not give a significant peak in their Fourier transform, which is typical for "pure" life-threatening arrhythmias.

To improve the quality of the features, describing such aperiodic signals, the use of Wavelet transform or high-order statistics can be a good choice.

5 CONCLUSIONS

The novel classifier dataset of two-second fragments of electrocardiograms containing all of the most common rhythm disorders has been created. The fragments were grouped into 6 classes according to the degree of their danger to human life.

Transition to two-class problem of separation of life-threatening arrhythmias from background rhythm and low-risk violations was made.

The resulting two-class problem was solved using kNN, LNCH, nearest mean and SVM with different kernels methods. As a result of the classification quality assessment, the low sensitivity of non-SVM methods was revealed.

After reviewing the objects that gave errors regardless of the algorithm used, 2 types of fragments were identified, which classification in the frequency domain seems difficult.

ACKNOWLEDGEMENTS

This research was supported by Russian Foundation for Basic Research (RFBR), research projects 19-29-01009 and 18-29-02036.

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