Detection of Irregular Heartbeats Using Tensors

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Abstract

Automatic classification of heartbeats in different categories is important for ECG analysis. The number of irregular heartbeats in a signal can for example be used as a risk stratifier for sudden cardiac death. Current heartbeat classification methods typically use time or frequency domain features to characterize heartbeats. We propose the use of tensors to incorporate the structural information that is present in multilead ECG channels. Since different ECG leads provide information on a particular orientation in space, more robust detection can be done if all leads are considered. After preprocessing and heartbeat detection using wavelet-based methods, the ECG signal is segmented beat-by-beat. The different heartbeats are then placed in a three-dimensional tensor with dimensions time, channels and heartbeats. Canonical Polyadic Decomposition is used to decompose the tensor. The results are three loading vectors, corresponding to the dimensions of the original tensor. Through analysis of these loading vectors, irregular heartbeats can be detected using a simple thresholding procedure. The method has been applied to a subset of the St.-Petersburg Institute of Cardiological Technics 12-lead Arrhythmia Database available on Physionet. When applying the method to the first 10 signals, we obtain a mean sensitivity and specificity of more than 90%. These results indicate that the presented method is a new and reliable way of performing irregular heartbeat detection.

1. Introduction

Cardiovascular diseases are a growing public health concern worldwide and a large number of people could benefit from a better and more reliable detection of cardiac dysfunction [1]. Heartbeat classification plays a major role in the identification of arrhythmias and thereby in assessing the risk of sudden cardiac death [2]. Heartbeats can be classified as normal or abnormal. An abnormal heartbeat is defined as any disturbance of the normal sinus rhythm. This can be a perturbation or abnormality in the rate, the regularity, the site of origin or the conduction of the electrical impulses of the heart.

Since manual analysis and interpretation of the ECG signal in long-term recordings is a time-consuming and tedious task, algorithms for automatic classification of heartbeats have been developed. During the last decades, techniques to improve this automatic heartbeat classification by computers have gained attention. The heartbeat classification problem is generally composed of three stages: preprocessing, feature extraction and classification. Various features, such as RR interval features [3–5], ECG morphology features [4, 6] and features drawn from the wavelet transform [7, 8] have been proposed to characterize the ECG. In these traditional heartbeat classification methods the ECG is typically represented as a vector. However, by representing the ECG as a tensor more structural information can be preserved. The application of tensor methods for heartbeat classification has been done before [9, 10]. However, these methods often require a training stage and more complicated optimization mechanisms. We propose a method that is based on tensor decomposition methods and where classification can be done using a simple thresholding procedure. Furthermore no training stage is necessary. The method is based on the same principle as used in tensor-based T wave alternans detection [11].

The rest of this paper is organised as follows. The data on which the methods have been evaluated will be described briefly. In the following section, the methodology of the proposed classification methods including the preprocessing stage will be presented. Next, the results will be presented and critically discussed. Finally, section 5 draws the conclusion of this work.

2. Data

A subset of the St.-Petersburg Institute of Cardiological Technics 12-lead Arrhythmia (INCART) Database was used for the evaluation of the developed methods. This database is available on PhysioNet [12] and contains 75

non-pacemaker recordings of 30 minutes at a sampling frequency of 257Hz. All signals were routine clinical 12 lead ECG signals. The signals were collected from 17 men and 15 women between 18 and 80 years old who were undergoing tests for coronary artery disease. Preference was given to recordings of patients with ECGs consistent with ischemia, coronary artery disease, conduction abnormalities and arrhythmias. Heartbeat annotations, computed by an automatic algorithm and manually corrected, are also provided.
Here, the first ten signals of the database have been used for evaluation. In total, the subset consists of 9257 normal and 470 abnormal heartbeats.

3. Methods

The tensor-based irregular heartbeat detection method consists of four steps. In the preprocessing stage, the noise is removed from the data before it is tensorized. After tensorization, the tensor is decomposed so the irregular heartbeats can be detected.

3.1. Preprocessing

In the preprocessing stage, both baseline wander and high frequency noise are removed from the ECG signal. Baseline wander removal is done channel-by-channel without introducing any signal distortion [13]. The high frequency noise is removed using wavelets.
Because the ECG signal has to be segmented into distinct heart cycles prior to tensorization, the locations of the R peaks need to be known. To make evaluation of the results feasible, the annotations provided with the database were used here.

3.2. Tensorization

An ECG signal typically is either a vector (single channel ECG) or matrix (multichannel ECG). In order to apply tensor decomposition methods, the ECG signal needs to be transformed into a tensor, e.g. *tensorized*. Tensorization can be done in many different ways. Since the main interest here are the differences between subsequent heartbeats, the ECG is tensorized by segmenting the signal in different hearbeats and stacking these heartbeats in a 3D manner. The 2D ECG signal with dimensions *channels x time* is transformed in a 3D tensor with dimensions *channels x time x heartbeats*. While the time dimension of the 2D ECG channel contains the total length of the ECG signal, the time dimension of the tensor only has the duration of one heartbeat.
The segmentation is done by taking a fixed-length interval around the R peak. The interval starts 200ms before the R peak and has a length of 500ms. The different segments are normalized before stacking them in the tensor by subtracting the mean and dividing by the standard deviation. If the heart rate differs greatly among the signal it may be necessary to apply resampling since it is important that the different waves of the ECG signal are largely aligned. Figure 1 illustrates the tensorization process.

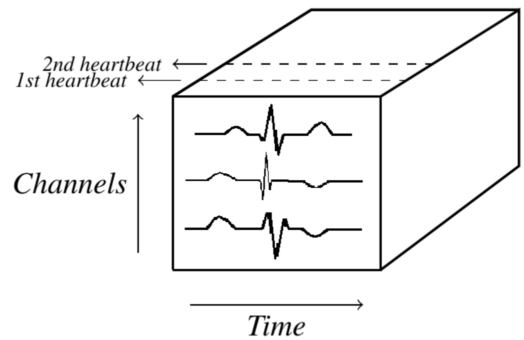

Figure 1: Tensorization of the ECG signal.

3.3. Tensor decompostion

Many tensor decomposition methods exist, all leading to factors with different ranks [14]. Here, Canonical Polyadic Decomposition (CPD) is used to decompose the tensor X in a sum of R rank 1-tensors:

$$X = \sum_{r=1}^{R} A_r \circ B_r \circ C_r \quad (1)$$

In this case, R, the rank of the decomposition, is chosen as 1 since we are interested in the main variation between different heartbeats.
The result is 1 rank-one tensor consisting of 3 loading vectors L_1, L_2 and L_3 which match the 3 dimensions of the original tensor. The first loading vector (L_1), corresponding to the *time* dimension, shows the average heartbeat over all heartbeats. The second loading vector L_2 (*channels*) is associated with the different heartbeat morphologies in different channels. L_3 corresponds to the *heartbeats* dimension.

3.4. Irregular heartbeat detection

The irregular heartbeats can be distinguished from normal heartbeats by examining the third loading vector L_3. When a heartbeat significantly differs from the mean heartbeat in the tensor (which can be known by looking at the second loading vector), this will be visible in the heartbeats vector. The value corresponding to an irregular heartbeat will be significantly higher than the value of a normal beat. A simple thresholding of the loading vector L_3 is used to discriminate the two classes. The threshold T is

$$T = \bar{L_3} + \sigma \qquad (2)$$

with σ the standard deviation of L_3. All heartbeats where L_3 is larger than T are marked as irregular heartbeats.

4. Results and Discussion

This section is divided into two parts. First the detailed results of one case study are described. Next the results for the complete datasets are summarized and discussed.

4.1. Case study

Figure 2a shows a sample of 1 lead of an ECG signal of 16 seconds. The sample contains 4 irregular heartbeats, indicated with a blue triangle. The normal heartbeats are marked with a red circle. If this sample is transformed into a tensor and the tensor is then decomposed as explained earlier, 3 loading vectors L_1, L_2 and L_3 are obtained. They are shown in Figures 2b, 2c and 2d.

Figure 2b shows the average heartbeat in this particular ECG sample. It is easily recognizable as a normal sinus heartbeat, which is expected since the majority of the heartbeats are normal. The morphology change over the different channels is visualized in Figure 2c. The 12 data points correspond to the 12 ECG channels. From this Figure we can conclude that for example the polarity of a signal varies greatly over different channels. Figure 2d is the most important Figure for irregular heartbeat detection since it shows the changes in the ECG over different heartbeats. The values of this loading vector for normal heartbeats varies around -0.04. The abnormal heartbeats are easily distinguishable by their higher values. The detection threshold T is indicated with a dotted line.

4.2. Results

The results for the complete dataset are summarized in Table 1. With a mean specificity of 0.9447 and mean sensitivity of 0.9110, we can conclude that the proposed method performs well. Upon further inspection of the sensitivity results, it is clear that the results are very good for most signals. For signal 7, the sensitivity result is NaN. This is because this signal did not contain any abnormal heartbeats. The poor sensitivity of signal 4 is due to the fact that the second part of the signal contains a lot of noise that is difficult to filter out. This causes the variation of the normal heartbeats to increase strongly, making proper thresholding difficult. If we remove the second part of this signal from the dataset, the sensitivity of signal 4 increases to 1 and the mean sensitivity to 0.9943. A more robust noise detection or noise removal algorithm could thus be useful when examining other datasets.

Signal index	Specificity	Sensitivity
1	0.9418	1
2	0.9458	1
3	0.9883	1
4	0.9094	0.25
5	0.9830	1
6	0.8956	1
7	0.9333	NaN
8	0.9906	0.9490
9	0.9129	1
10	0.9459	1
Mean	0.9447	0.9110

Table 1: Sensitivity and specificity results for INCART database.

In this study, only a distinction between a normal and an abnormal class is made. The abnormal heartbeats can be further divided into a number of different subclasses such as supraventricular and ventricular beats. In order to do this, an additional step is required. This could also help to remove some of the false positive detections, e.g. normal beats that are misclassified as abnormal which would lead to an extra increase in specificity results.

5. Conclusion

This paper presents a new method to detect abnormal heartbeats in multichannel ECG signals through the use of tensors. The method leads to very good results when evaluated on a subset of the INCART database. Further research is necessary to improve noise removal and to accomplish further classification of abnormal heartbeats in different subclasses. However, the current preliminary results indicate that this method is a promising tool for automatic beat classification.

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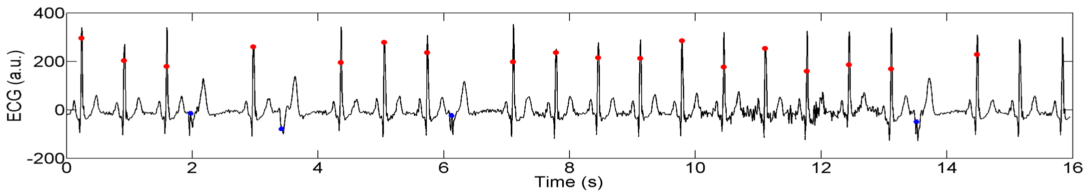
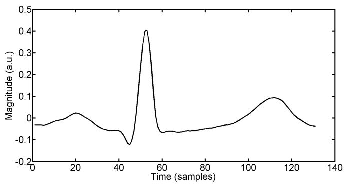
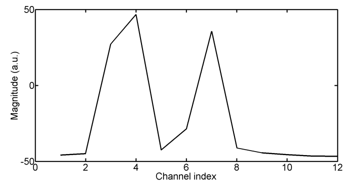


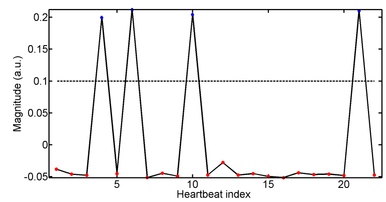
(a) Sample ECG signal with normal (red) and abnormal (blue) heartbeats.



(b) First loading vector (time).



(c) Second loading vector (channels).



(d) Third loading vector (heartbeats) with normal (red) and abnormal (blue) beats.

Figure 2: Resulting loading vectors after CPD

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