Irregular Heartbeats Detection using Tensors and Support Vector Machines

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Abstract

The automatic analysis of Heart Rate Variability in records of ambulatory electrocardiogram (AECG) requires the detection of irregular heartbeats which cannot be included in the analysis. This article presents a novel approach for detecting irregular beats using tensors and Support Vector Machines.

After signal filtering, for each record of the database a third order tensor was constructed. Next, a rank-3 Canonical Polyadic Decomposition (CPD) was applied. CPD yields three loading matrices corresponding to the modes space (channel), time course and heartbeats respectively. The heartbeat mode matrix was used as the input of a linear Support Vector Machine (SVM) classifier. The SVM was trained for classifying between irregular and normal heartbeats. The training set was randomly selected from the 2% of the patterns in each record.

The classifiers show a global accuracy of 97.2%. The results suggest that this approach is a promising method for detecting irregular heartbeats.

1. Introduction

In the last years, there has been an increasing interest in the study of the Heart Rate Variability (HRV) using the electrocardiogram (ECG). The HRV is modulated by both sympathetic and parasympathetic branches of the autonomic nervous system. HRV analysis during short (5 minutes) and long (up to 24 hours) periods of time provides relevant information about certain diseases and dysfunctions of the cardiovascular and nervous systems [1].

The ambulatory ECG (AECG) or Holter monitoring is a medical test where the ECG is continuously monitored for a period of 24 to 48 hours. HRV analysis is valid if and only if each detected QRS complex belongs to a completed heartbeat originated in the sinoatrial node (SA) [2]. If this is not the case, the beat should be excluded from the HRV analysis. Therefore it is crucial to perform a manual or automated morphological recognition of beats in order to select the valid beats and reject the invalid ones.

A large amount of data is obtained during a 24h AECG or Holter measurement. Since visual analysis of such amount of data is a time-consuming task, several automated computer-based methods for ECG analysis have been described in the literature [3-5]. This paper presents a novel approach for detecting irregular heartbeats using tensors and Support Vector Machines (SVM).

2. Materials and methods

Figure 1 shows a diagram of the developed ECG signal classification diagram method. In the next sections, first the dataset is described. Then, each block of the diagram is briefly discussed.

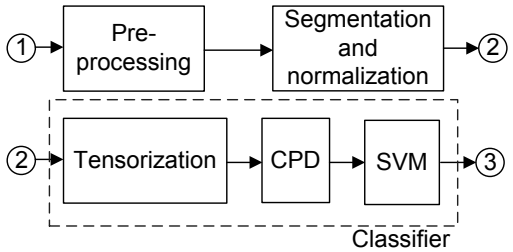


Figure 1. Tensor based method for irregular heartbeat detection using CPD and SVM.

2.1. Data

The dataset is the database from St.-Petersburg

Institute of Cardiological Technics 12-lead Arrhythmia Database (INCARTDB) available on Physionet [6]. INCARTDB consists of 75 annotated recordings extracted from 32 Holter records. Each record is 30 minutes long and contains 12 standard leads. The sample frequency is 257 Hz. Table 1 shows the distribution of the heartbeat classes along the entire database.

Table 1. INCARTDB classes distribution.

Normal (%)	PVC (%)	Other (%)
87.30	11.38	1.32

In this study, only two classes were considered; the normal class **(N)ormal** and the abnormal class **(A)bnormal** which includes the PVCB type and the rest of the irregular beats.

2.2. Pre-processing and segmentation

The pre-processing block is divided in two stages: (1) elimination of baseline wander and (2) high frequency noise filtering. The first stage uses median filtering [7] and the second one uses a wavelet filter with a hard thresholding approach [8].

The median filter uses two window sizes, 200 ms and 600 ms. The first window eliminates the P waves and the QRS complexes of each heartbeat. The second window eliminates the T wave. After removing the physiological waves the resulting signal is considered as baseline wander. Next, it is subtracted from the original ECG to eliminate the baseline drift.

The second stage filters out the high frequency noise. First, the Discrete Wavelet Transform (DWT) of the signal is computed. This process decomposes the signal into four levels using the Daubechies 4 (db4) as a mother wavelet. After the signal decomposition, both detail coefficients 1 and 2 are filtered using thresholds for each level. Finally, the signal is reconstructed using the inverse DWT (IDWT) [8].

Next, the ECG signal is segmented into different beats by taking a window around each R-peak. In this paper we have used the R-point annotations provided in the database. The length of the (asymmetric) segmentation window is equal to 131 samples including the R-peak point. It starts 50 samples (195ms) before each R peak and selects 80 more samples (310 ms) after each peak. Each beat was normalized by subtracting the average value and dividing by the standard deviation.

2.3. Tensorization and CPD

Here we use a tensor approach for representing the ECG signal. The use of tensors is a natural choice for representing 12-lead ECG signals because it preserves the structural information contained in a beat i.e. it allows to treat each beat as a matrix which contains the information of all standard leads. The process of transforming the signal into three-way arrays (tensors) is called tensorization. The process consists of arranging each heartbeat (12 leads) in the record one after other

The constructed tensor has three modes. The first mode is the space, i.e. the channels, the second one is the time course, and finally the last mode is the heartbeat. Each beat is stacked in order, see Figure 2. The result is one third-order tensor for each record in the database.

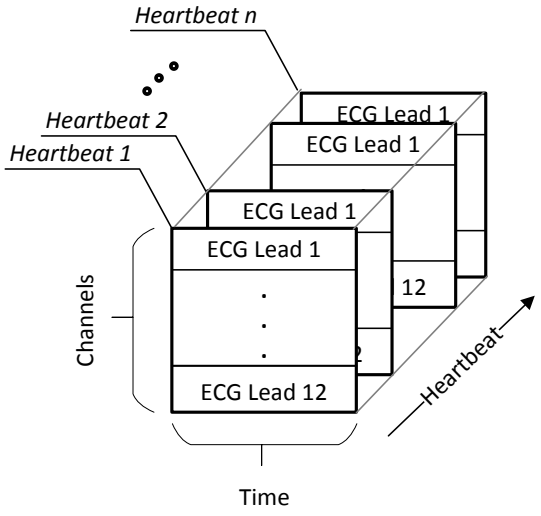


Figure 2. Tensorization process.

Canonical Polyadic Decomposition (CPD) [9] decomposes the tensor $\boldsymbol{\mathcal{X}} \in \Re^{I_1 \times I_2 \times I_3}$ as a minimal sum of R rank-1 tensors,

$$\boldsymbol{\mathcal{X}} = \sum_{r=1}^{R} \mathbf{u}_1^{(r)} \otimes \mathbf{u}_2^{(r)} \otimes \mathbf{u}_3^{(r)}, \qquad (1)$$

where R is the rank of the tensor $\boldsymbol{\mathcal{X}}$.

The criterion for selecting the correct rank is based on the mean relative error behaviour for different R values. For each record we computed the mean relative error (mre) varying R in the range (1-20). Then we plotted each graph of mre vs R. Figure 3 shows the mean relative error with respect to the rank of the CPD for the whole database. The figure was obtained by averaging the graphs of each individual record. As expected, the mean relative error monotonically decreases with the rank of the CPD. The error value drops below 20% when $R \geq 12$.

However, the error drop between orders six and twelve is only of 5%, and smaller for the range (12-20). Conversely, the mean relative error decreases approximately 30% from one to five components. Furthermore, the improvement in the mean relative error

is below 5% when the number of rank-1 terms in the CPD increases from three to four. By contrast, the first two differences are 17.56% and 12.05% respectively. This suggests three as the appropriate number of rank-1 terms.

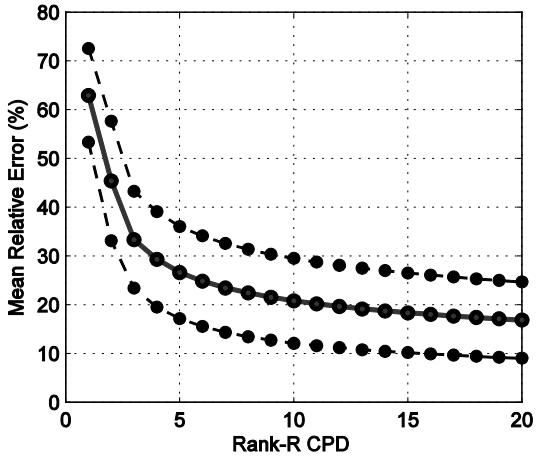


Figure 3. Mean relative errors in a Rank-R CPD ($1 \leq R \leq 20$), all records in the database were included. Both dashed-lines represent $\pm\sigma$ respectively

The rank-3 CPD yields three loading matrices corresponding to space (channel), time course and heartbeat mode respectively. The heartbeat mode matrix $\mathbf{H} \in \Re^{I_3 \times 3}$ will be used as the input of the SVM classifier.

2.2. SVM

This paper uses a binary linear SVM for classifying. We have chosen the linear classifier because it is simpler and faster than the nonlinear ones. The main drawback is that non-linearly separable datasets will degrade the performance.

The classifiers were created, trained and tested using LIBSVM [10]. A very useful feature of LIBSVM is the inclusion of weighted SVM for dealing with unbalanced data. Owing to the balance ratio between classes in INCARTDB is close to seven, we suggest a weight value in the range (3-7). The results below were obtained with a weight value of five.

Here, we followed a "by record" training and testing strategy. The term "by record" means that the training and testing processes are done for each record. The training process randomly takes the 2% of the beats in the record; the ratio among classes is kept. We use a low percentage for training to allow a user to build the training set manually in a future implementation. In such conditions it is desirable that small training sets guarantee high classification performances.

The performance evaluation for the classifier was carried out by computing four indexes in the testing set: Sensitivity (Se), Specificity (Sp), Positive Predictive Value (Ppv) and Accuracy (Acc).

3. Results and discussion

Tables 2 and 3 show the global confusion matrix and the performance indexes of the classifiers respectively. Table 2, was obtained by summing the confusion matrix of each record. Record 61 was omitted from the database since it only contains 1 irregular beat. Hence, it is not possible to build training and testing sets using the 2%-98% ratio.

Table 2. Global confusion matrix for all classifiers. Classes **(A)bnormal** and **(N)ormal**.

Output/Target	A	N
A	20530	3421
N	1333	145666

Table 3. Global performance indexes for all classifiers.

Se(%)	Sp(%)	Ppv(%)	Acc(%)
93.90	97.70	85.72	97.22

We also examined the performance at record level under two conditions; imbalanced and well-balanced datasets. The first example corresponds to the record 36 of the database. This record has 3449 **(N)ormal** and 462 **(A)bnormal** heartbeats yielding a balance ratio of 88%-12%. The test results for this record are shown in Tables 4 and 5. The method shows an acceptable performance.

Table 4. Confusion matrix for the classifier trained and tested with record 36 (imbalanced dataset).

Output/Target	A	N
A	387	47
N	66	3333

Table 5. Performance indexes for the classifier trained and tested with record 36 (imbalanced dataset).

Se(%)	Sp(%)	Ppv(%)	Acc(%)
85.43	98.61	89.17	97.05

The second example corresponds to the record 31 which has 1844 (**N)ormal** and 1366 **(A)bnormal**

heartbeats yielding a balance ratio of 57%-43%. The performance indexes are also good for this record, see Tables 6 and 7.

Table 6. Confusion matrix for the classifier trained and tested with record 31 (well-balanced dataset).

Output/Target	A	N
A	1332	24
N	7	1783

Table 7. Performance indexes for the classifier trained and tested with record 31 (well-balanced dataset).

Se(%)	Sp(%)	Ppv(%)	Acc(%)
99.48	98.67	98.23	99.01

As can be seen from the tables above, the classifier has a good performance under both imbalanced and balanced conditions. However, in records with majority of Atrial Premature Beats (APB) such as records 33 (591 APB) and 34 (536 APB) the classifier shows the worst performances (Sp = 0%). A possible explanation for this behaviour might be that Normal and APB heartbeats are not linearly separable. In future investigations it might be possible to use fine tuned nonlinear SVM in order to address these difficult cases.

To conclude, the findings of this study suggest that the use of tensors and tensor decompositions in combination with SVM is feasible for detecting irregular heartbeats. Moreover, the method has the advantage to deal with high dimensionality data in a simple and aesthetic way.

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