Tensor-based Detection of T Wave Alternans in Multilead ECG Signals

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Abstract

In this study, a new method for the detection of T wave alternans in multichannel ECG signals is introduced. The use of tensors (multidimensional matrices) allows us to combine the information present in all channels, making detection more robust. To construct a 3D tensor from a 2D ECG signal, the T wave is first roughly segmented. The intervals are then placed after each other to obtain a 3D structure with dimensions time, space and heartbeats. The tensor is decomposed using Canonical Polyadic Decomposition. The result is 1 rank-one tensor consisting of 3 loading vectors (which match the 3 dimensions of the original tensor). The third loading vector corresponds to the heartbeats dimension and gives information about the behavior of the T wave in different heartbeats. The Fourier transform of this loading vector can then be used to examine the presence of TWA. The methods have been tested on a subset of the T wave alternans database available on Physionet. Results show a very clear distinction between loading vectors of signals from both groups: the power of the loading vector in the TWA group is on average 100 times larger than in the control group. This suggests that tensors are an effective way of detecting TWA in multilead signals.

1. Introduction

T wave alternans (TWA) is a periodic variation in the amplitude of the T wave, typically in a ABAB-pattern. It is a widely recognized indicator for sudden cardiac death [1]. When the amplitude difference between two T waves is large enough, TWA can be detected by visually inspecting the electrocardiogram (ECG). In many cases however, the amplitude difference is only a few microvolts which is too small for visual detection to be reliable enough. This is also referred to as microvolt T wave alternans [1].
Several TWA detection methods exist, the most common ones are the spectral method [2] and the modified moving average method [3]. Most of the existing methods are developed to analyze single channel ECG signals. When multiple channels are available there are two possibilities. The channels can either be processed independently and the results can be combined in a later stage, or the information available in the channels can be combined and analyzed as a whole. This can be done for example by constructing a combined lead from all channels or by using Principal Component Analysis [4].
In this study, we use tensors to detect T wave alternans in multichannel ECG signals. Tensors are multidimensional arrays which allow to analyze information in multiple dimensions. In this case, it is possible to simultaneously process all channels of the ECG signal while looking at different heartbeats. This way all the information present in the signal is combined, which leads to robust results.
Tensorlab is used for the tensor computations and decompositions. It is a Matlab-based toolbox that contains many different methods for tensor calculations and structured data fusion [5].

2. Methods

2.1. Data

The data used in this study are taken from the T wave Alternans Challenge Database that is available on Physionet and that has been constructed for a previous CinC challenge [6] [7]. It contains 100 multichannel ECG records of 2 minutes with varying amounts of TWA. The database is composed of both records from other ECG databases and artificial records with simulated TWA. A subset of 20 records is selected from this database by selecting the 10 records with the highest amount of TWA (as defined by the ranking available on Physionet) and the 10 records with the lowest amount of TWA, which do not contain TWA. All signals have a sampling frequency of 500 Hz. The number of channels varies between 3 and 12.

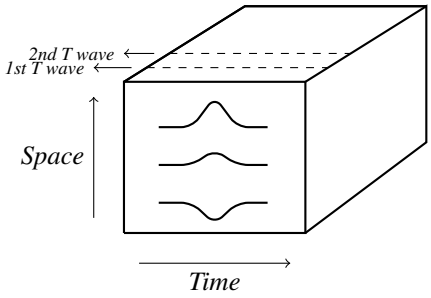


Figure 1: Construction of the T wave tensor.

2.2. Preprocessing

Since many ECG signals contain a significant amount of baseline shift, the baseline has to be removed so it does not alter the amplitude of the T wave. This is done with the method described in [8]. First, the QRS complexes are detected using a wavelet-based method [9]. Starting from the QRS complexes, fiducial points are then located on a flat piece of the ECG signal. By interpolating a quadratic spline through the fiducial points, the baseline can be approximated. Subtracting this spline from the original signal removes the baseline drift without changing other signal characteristics.

2.3. Tensor construction

A tensor is a higher-dimensional matrix, while an ECG signal typically has only 2 dimensions: *space x time*. In order to apply tensor methods on matrices, the signal first has to be tensorized. Tensorization adds one or more extra dimensions to the original signal. Here, a third dimension is created by aligning all T waves. This means that for this application instead of adding information to the ECG signal to construct a tensor, the most important parts of the signal are extracted and ordered in a tensor. To avoid complete T wave detection (which is prone to errors and sensitive to noise) only a rough T wave segmentation is done. An interval of 250 ms is selected from 100 to 350 ms after each R peak. These intervals are then placed one after the other in a 3D structure. The result is a tensor with 3 dimensions: *space x time x heartbeats*.

Figure 1 illustrates the complete tensor construction.

2.4. Tensor decomposition

The tensor is decomposed with Canonical Polyadic Decomposition (CPD) [10]. CPD will decompose a tensor X in a sum of R rank 1-tensors:

$$X = \sum_{r=1}^{R} A_r \circ B_r \circ C_r \tag{1}$$

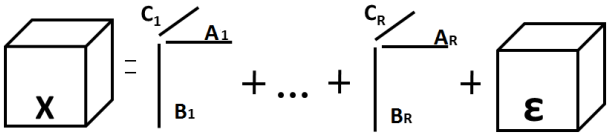


Figure 2: Canonical Polyadic Decomposition

The process is illustrated in Figure 2. In this case, R, the rank of the decomposition, is chosen as 1.

The result is 1 rank-one tensor consisting of 3 loading vectors (which match the 3 dimensions of the original tensor). The first loading vector, corresponding to the *time* dimension, shows the average T wave over all heartbeats. The second loading vector (*space*) is associated with the change in the shape and amplitude of the T wave over the different channels. The third loading vector corresponds to the *heartbeats* dimension. It gives information about the behaviour of the T wave in different heartbeats. This loading vector will change when there is TWA present and can thus be used for TWA detection.

2.5. TWA detection

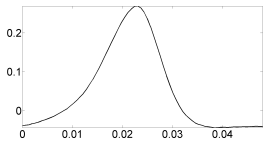
To effectively detect T wave alternans, the third loading vector C is used as is explained in paragraph 2.4. When TWA is present, the typical ABAB-pattern that exists in the amplitude of the T wave will also be visible there. It is quantified by calculating the K-score, the Fourier transform of the vector and calculating the power at 0.5 cycles per beat (CPB), which is also used in the widely used spectral method [2]. To correct for the presence of noise, this value is divided by the mean power in the noise band (0.44-0.48 CPB):

$$\text{K-score} = \frac{0.5CPB}{mean(0.44CPB - 0.48CPB)} \tag{2}$$

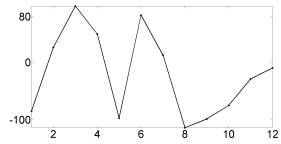
The value of the K-score will increase when TWA is present.

3. Results

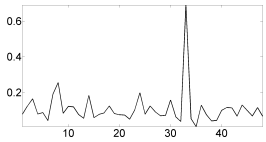
An example of the different loading vectors resulting from CPD is shown in Figure 3. Figure 3a and 3b show respectively the *time* and *channels* vector. The first vector represents the average T wave shape in the complete signal and clearly resembles a T wave. The second vector shows the distribution of the T wave over different channels. From this vector certain T wave characteristics can be derived. An example is the T wave polarity in a particular channel, which will be negative when the value of the loading vector is smaller than zero and positive when it is larger than zero.



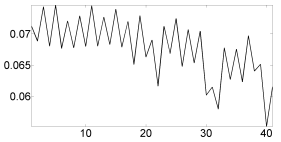
(a) First loading vector A (time)



(b) Second loading vector B (space)



(c) Third loading vector C without TWA



(d) Third loading vector C with TWA

Figure 3: Resulting loading vectors after CPD

Figure 3c and 3d show the third loading vector for two signals: one 'healthy' signal without TWA (3c) and one signal where there is TWA present (3d). The difference between both vectors is remarkable. Both vectors show variations in T wave amplitude, but the typical ABAB-pattern that characterizes TWA is only visible in the vector with TWA. The variations that are present in the first vector show the natural differences in T wave amplitudes and are of no further importance.

	Min K-score	**Max K-score**
No TWA	0.0042	0.6691
High TWA	18.6734	464.8841

Table 1: K-scores for all signals

Table 1 summarizes the K-scores for all the signals used in this study. The difference between both groups (signals with and without TWA) is very large: the K-score of the signals which contain T wave alternans is at least 30 times higher than the K-score of the signals without T wave alternans.

4. Discussion

TWA detection is known to be a difficult task. The results from the previous section show that the method presented in this paper succeeds very well in detecting T wave alternans. Both by inspecting the results of Figure 3c and 3d and Table 1 the difference between signals with and without TWA is clear. The K-scores of both groups show differences of an order of magnitude. However, the current results are only preliminary. The signals used in this study either contain no TWA or a very large amount of TWA. For further proof of the accuracy of the detection, the subset should be expanded with signals that for example contain smaller amounts of TWA.

Tensors, although very popular in chemometrics and psychometrics, have rarely been used for the processing of ECG signals. A first step when using tensor methods is the construction of the multidimensional tensor from the 2-dimensional ECG signal. Here, this is done in a very basic way by taking a fixed interval after the detected QRS complex. While it works well for this set of signals, this will however not be sufficient to work in all cases. When the heart rate for example increases or decreases significantly, the fixed interval will not necessarily contain the T wave which is essential to obtain correct results. A solution could be to dynamically adapt the interval length to changes in the heart rate or to detect the begin and end of the T wave and take an interval around it.

At the moment, only TWA detection has been done. The next step would be to use the presented method to quantify the amount of T wave alternans present in the signal. This way a distinction can be made between signals with a high and a low amount of TWA. In this context it would also be interesting to investigate the effect of the presence of noise on the obtained results.

5. Conclusion

The method presented in this paper uses tensors to detect T wave alternans in multichannel ECG signals. The obtained results show a very clear distinction between signals with and without TWA. Although further work is necessary to generalize the findings, it has been demonstrated that tensors can be used successfully to analyze multichannel ECG signals.

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