Tensor-based detection of T wave alternans using ECG

Griet Goovaerts[1], Bert Vandenberk[2], Rik Willems[2] and Sabine Van Huffel[1]

***Abstract*— T wave alternans is defined as changes in the T wave amplitude in an ABABAB-pattern in T wave amplitude. It can be found in ECG signals of patients with heart diseases and a possible indicator to predict the risk on sudden cardiac death . Due to its low amplitude, robust automatic T wave alternans detection is a difficult task. We present a new method to detect T wave alternans in multichannel ECG signals. The use of tensors (multidimensional matrices) permits the combination of the information present in different channels, making detection more reliable. The possibility of decomposition of incomplete tensors is exploited to deal with noisy ECG segments. Using a sliding window of 128 heartbeats, a tensor is constructed of the T waves of all channels. Canonical Polyadic Decomposition is applied to this tensor and the resulting loading vectors are examined for information about the T wave behavior in three dimensions. T wave alternans is detected using a sign change counting method that is able to extract both the T wave alternans length and magnitude. When applying this novel method to a database of patients with multiple positive T wave alternans tests using the clinically available spectral method tests, both the length and the magnitude of the detected T wave alternans is larger for these subjects than for subjects in a control group.**

I. INTRODUCTION

Sudden cardiac death (SCD) is the second most important cause of death in Western-Europe. When analyzing electrocardiograms (ECGs), T wave alternans (TWA) is a feature that is used to determine whether someone is at risk for life-threatening arrhythmic events [1]. It is defined as an alternating pattern in T wave amplitude. Large and small T waves follow each other in an ABABAB-pattern. When two subsequent T waves are very different in amplitude, T wave alternans can be detected by visually inspecting the signal. The difference between two subsequent T waves may however be as small as a few microvolts, making visual detection impossible. This type of TWA is typically called microvolt T wave alternans [1].

T wave alternans is widely studied and many (semi)-automatic detection methods exist. The most commonly used method in medical practice is the spectral method [2]. Other methods are the correlation method [3] and moving modified average method [4].

Since ECG signals are often measured with only one channel, most methods are not specifically developed to deal with multichannel ECG signals. When multiple channels are present however, they provide extra information that should be included in the analysis. To extend single-channel analysis to multiple channels, two possible options exist. A first option is to detect TWA channel-by-channel and later combine the results. A second option is to first combine the different channels and analyse them as a whole. An example is to construct a combined lead from all channels or by performing Principal Component Analysis [5].

A common problem in TWA detection methods is the presence of noise. Since the T wave amplitude is often relatively small compared to the amplitude of the QRS complex, even small amounts of noise can already completely mask the T wave, making reliable TWA detection difficult.

We present a novel method to detect T wave alternans in multichannel ECG signals using tensors. Tensors (structures with more than two dimensions) allow a simultaneous analysis of a signal in multiple dimensions. In this case, this means that all channels and heartbeats can be included and studied in one tensor. Also, since tensor decompositions of incomplete tensors can still lead to reliable results, this can be a solution to deal with noisy parts in the ECG signals. A first version of this method was already presented in [6]. This method however is adapted to detect transient TWA in longer signals and to deal better with noisy recordings. Furthermore the method is now applied to a dataset of real subjects.

Tensorlab is used for the tensor computations and decompositions. It is a Matlab-based toolbox that contains many different numerically optimized methods for tensor calculations and structured data fusion [7].

II. DATA

The results presented here are obtained by applying the method to a dataset from the University Hospital Leuven. The dataset includes 33 Holter ECG signals between 14 and

* Research supported by Research Council KUL: CoE PFV/10/002 (OPTEC); FWO: PhD/Postdoc grants. iMinds Medical Information Technologies: SBO- 2015, ICON: NXT _ Sleep; Belgian Federal Science Policy Office: IUAP P7/19/ (DYSCO, 'Dynamical systems, control and optimization', 2012-2017); Belgian Foreign Affairs-Development Cooperation: VLIR UOS programs (2013-2019); EU: European Union's Seventh Framework Programme (FP7/2007-2013); EU MC ITN TRANSACT 2012, 316679; ERASMUS EQR: Community service engineer , 539642-LLP-1-2013; Other EU: INTERREG IVB NWE programme RECAP 209G; European Research Council: ERC Advanced Grant, 339804 BIOTENSORS This paper reflects only the authors' views and the Union is not liable for any use that may be made of the contained information. The research leading to these results has received funding from the European Communitys Seventh Framework Program FP7: EU-CERT-ICD (grant agreement no. HEALTH-F2-2013-602299). RW receives research funding from Biotronik, Boston Scientific Belgium and Medtronic Belgium. RW has received speakers- and consultancy fees from and participated in clinical trials by different manufactures of cardiac implantable electronic devices (Medtronic, Boston Scientific, Biotronik, St Jude Medical, Sorin).

[1]G. Goovaerts and S. Van Huffel are with the Department of Electrical Engineering-ESAT, STADIUS, KU Leuven and iMinds Medical Information Technologies Department, Leuven, Belgium. griet.goovaerts@esat.kuleuven.be

[2]B. Vandenberk and R. Willems are with the Department of Cardiovascular Science, KU Leuven and the department of Cardiology, University Hospital Leuven.

23 minutes long from nine subjects. Subject were selected based on the results of a clinical TWA test (Cambridge Analytic Spectral method). Only subjects with multiple consistent positive or negative tests were included in the dataset. Thirteen signals from four subjects were labelled positive, twenty signals from five subjects negative.
All ECG signals are recorded with a sampling frequency of 256 Hz. Most records have three ECG channels, some only include two channels. The signals are all between 14 and 23 minutes long.

III. METHODOLOGY

A. Preprocessing

The presence of noise in the ECG signal can heavily influence the result of any TWA detection method. Both high frequency noise and low frequency baseline drift have to be considered in the preprocessing stage. It is crucial that the signal is not distorted during this stage, since this could have a serious influence on the final result.
The first preprocessing step is a low-pass filter with cut-off frequency 60 Hz to remove high frequency noise. Because the spectral content of the T wave is typically limited to 40 Hz [8], this will normally not affect the T wave amplitude and shape. The signals are then normalised channel-by-channel by subtracting the mean value and dividing by the standard deviation.
R peak detection is then done by applying the wavelet-based method described in [9]. In order to minimize the effect on the signal quality, the baseline drift is removed with quadratic spline interpolation. Starting from the detected R peaks, fiducial points are detected that are located on a flat piece of ECG signal. The baseline drift in the signal can then be approximated by interpolating a quadratic spline through these points. The subtraction of the spline from the original signal results in the removal of the baseline drift without distorting the different ECG waves.

B. T wave segmentation

In order to also detect transient T wave alternans (i.e. TWA which is not constant in time), a moving window of length 128 heartbeats is used to analyse the signals. First the number of irregular heartbeats in each channel is examined. There are three main causes for irregular heartbeats:

1) The presence of different types of heartbeats such as PVCs.
2) An error during the QRS detection can lead to detection of the T wave. Segmentation would lead to wrong results in that case.
3) Presence of noise in one or more channels.

The first two causes lead to an unreliable heartbeat in all channels, while the third often causes an irregular heartbeat in only one or two channels. Irregular heartbeats are thus detected channel-by-channel by calculating the correlation between each QRS complex and the mean QRS complex of the window of interest. If the correlation is smaller than 0.7, the heartbeat is marked as irregular. When the number of irregular heartbeats exceeds 25 the window is discarded completely.
T wave segmentation is done by selecting a fixed-length interval after the QRS complex. The start of the interval is fixed at 100 ms after the detected R peak. Since changes in heart beat can have an effect on the length of the ST complex, the length of the interval l is dependent on the mean RR interval over the window:

$$l = 1.3\sqrt{|RR|} \tag{1}$$

In this Equation, RR is the mean RR interval calculated over the current window of 128 beats. After this prior segmentation the T waves are further aligned by shifting the start point of the segmentation interval up to 30 ms and calculating the cross-correlation between the T wave and a template (the mean T wave over the window calculated from the initial segmentation). The final segmentation window starts at the point which corresponds to the maximum correlation value.

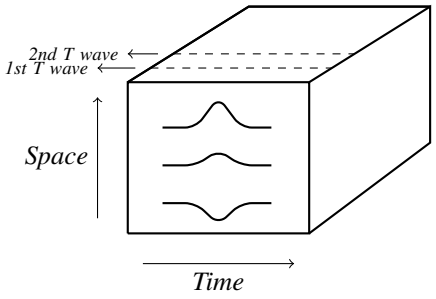


Fig. 1: Construction of the T wave tensor.

C. Tensor construction

Tensors are multidimensional structures while the ECG signal has only two dimensions: *channels x time*. Tensorisation transforms a 2D signal to a tensor by adding (an) extra dimension(s). Here, a third dimension, *heartbeats*, is created by aligning all T waves. A 3D structure is formed which can be represented by a cube, with in each slice the different T waves of one heartbeat in the different ECG channels. Figure 1 illustrates the tensorisation process.

One of the advantages of tensor decomposition methods is the possibility of decomposing incomplete tensors. Incomplete tensors are tensors where not all values are known prior to the decomposition. We take advantage of this possibility by omitting the T waves from the irregular heartbeats detected in the preprocessing stage and setting their value as unknown. However, since simulation results suggest that the signal of at least one channel is needed for reliable results, the irregular T wave is replaced by the mean T wave in that window if the heartbeat is irregular in all channels. Practically this means that irregular heartbeats that are present because of arrhythmias and errors during R peak detection will be removed, while the T waves partially corrupted by noise will be included in the tensor. The final result is then an *incomplete* tensor of three dimensions: *time x space x heartbeats*. The size of this tensor is the number of channels x l (calculated using Eq. 1) x 128 (the number of heartbeats in one window).

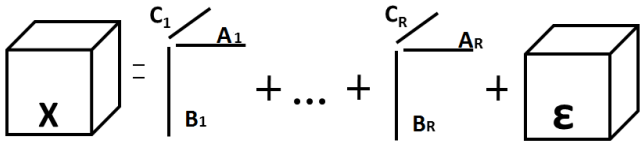


Fig. 2: Canonical Polyadic Decomposition

D. Tensor decomposition

The tensor is decomposed with Canonical Polyadic Decomposition (CPD). CPD decomposes a tensor X in a sum of R rank 1-tensors:

$$X = \sum_{r=1}^{R} A_r \circ B_r \circ C_r \tag{2}$$

This is illustrated in Figure 2. Since we are interested in the main variation of the T wave, the rank of the decomposition R is chosen as 1.

The result of CPD is a rank 1-tensor which consists of three loading vectors, corresponding to the three dimensions of the tensor: *space x time x heartbeats*. The size of each loading vector is equal to the size of the corresponding tensor dimension. While the first and second loading vector give information about the behavior of the T wave in respectively space and time, for T wave alternans detection mainly the third loading vector is important.

E. T wave alternans detection

To effectively detect T wave alternans the third loading vector is used, as explained in the previous paragraph. If there is TWA in the signal, the typical ABABAB-pattern that is present in the T wave amplitude will also be visible in the loading vector. To detect TWA, the sign changes in the loading vector are counted. Since noise also causes variations in the T wave amplitude, a minimum number of 10 consequent sign changes have to occur for a segment to be detected as a TWA episode to avoid false positive detections. The TWA can be quantified by calculating the mean difference between two TWA values in the loading vector. The total amount and amplitude of T wave alternans in a window can then be calculated by summing the length and amplitude of different TWA episodes in a window.

IV. RESULTS AND DISCUSSION

This section is divided into two parts. First the detailed results of two case studies (one positive and one negative) are described. Next the results for the complete datasets are summarized.

A. Case studies

Figure 3a shows a sample of ten seconds of an ECG signal after the preprocessing stage. The start and end points of the segmentation windows are indicated with a vertical line. This segment contains no irregular heartbeats, so the tensor construction will results in a complete tensor. After tensorization and tensor decomposition of this signal, the resulting loading vectors can be examined. In Figure 3b and 3c, the first and second loading vector are shown. They show the T wave in respectively time and space. The time vector corresponds to the average T wave in that window. The spatial vector gives information about the polarity and magnitude of the T wave. If we compare Figure 3a and 3c, it is clear that the T wave is negative in channel 1 and positive in channel 2 and 3. This can also be derived from inspecting the loading vector: The value corresponding to the first channel is positive, the third value negative. Channel 2 and 3 both have positive T waves, but here their magnitude differs which can also be concluded from Figure 3c.

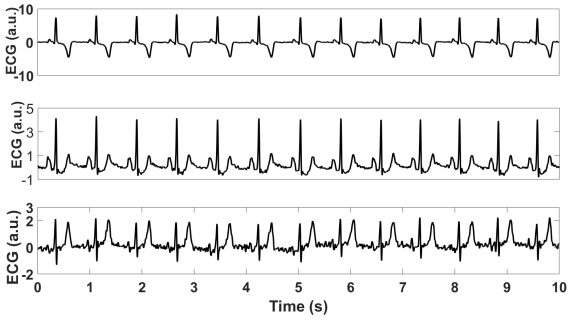
T wave alternans can be detected by analysing the third loading vector. Figure 3e and 3d show this loading vector for a signal without TWA and with several TWA episodes. On Figure 3e we see that, although there is a certain variation, no clear pattern is visible. The typical ABABAB-pattern is however clearly visible on Figure 3d, where the different TWA episodes are marked with green rectangles. By counting the sign changes as explained in Section III.e, a total of four TWA episodes could be detected with a total length of 59 heartbeats.

B. Results

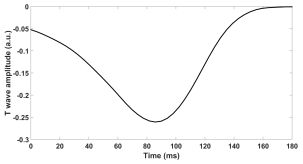
As discussed in Section III-A, windows with more than 20 irregular heartbeats are discarded. When analysing the complete dataset, in 5 signals more than 50 percent of the windows were discarded in this way. Since this is a sign of bad signal quality, these signals are not included in the results. The final dataset then consists of 11 signals with TWA and 17 control signals.
When analysing the presence of TWA in a window, we can look at 2 markers:

1) Length: the total length of all TWA episodes in a window of 128 heartbeats.
2) Magnitude: the average difference between two heartbeats in a TWA episode.

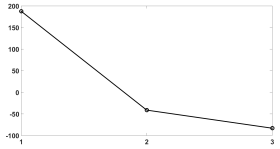
The difference in length is especially clear when looking at windows with a total TWA length of at least 25 heartbeats. 73 percent of the positive signals have at least one window with a minimal TWA length of 25. In the control group this is only the case for 2 signals or only 11 percent of all signals. When examining the TWA magnitude in both groups, there are also clear differences. In signals with TWA the maximum TWA magnitude is on average 50 percent higher than in the control group (0.12 versus 0.08).
Since the signals are normalized in the preprocessing step, the amplitude derived with this method does not necessarily correspond one-on-one with the microvolt value from the ECG signal. A database where the exact T wave alternans value is known is needed to calculate this conversion.
Although in this case the focus lies on alternans of merely the T wave, other types as alternans such as ST alternans or QRS alternans can be evaluated easily by constructing a tensor consisting of other ECG segments.



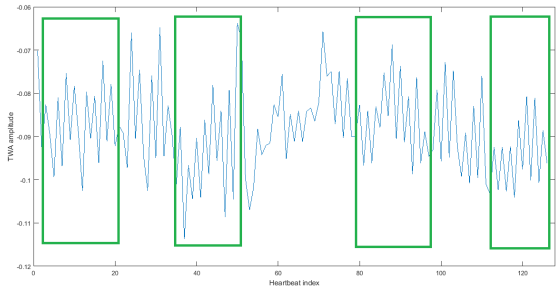
(a) ECG sample



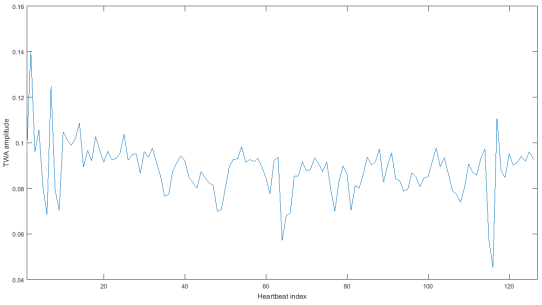
(b) First loading vector (Time)



(c) Second loading vector (space)



(d) Third loading vector with TWA.



(e) Third loading vector without TWA.

Fig. 3: Detailed results of TWA detection.

V. CONCLUSION

This paper presents a novel tensor-based method to detect T wave alternans in multilead ECG channels. The method uses tensors and tensor decompositions to make optimal use of the information in different channels. Incomplete tensors are used to deal with noisy segment and irregular heartbeats. Both T wave alternans length and magnitude can be examined and results on a hospital dataset show that a clear distinction can be made between TWA positive subjects and controls using the clinically spectral method.

REFERENCES

[1] Ikeda, Takanori, et al. "Predictive value of microvolt T-wave alternans for sudden cardiac death in patients with preserved cardiac function after acute myocardial infarction: results of a collaborative cohort study." Journal of the American College of Cardiology 48.11 (2006): 2268-2274.

[2] Bloomfield, Daniel M., Stefan H. Hohnloser, and Richard J. Cohen. "Interpretation and classification of microvolt T wave alternans tests." Journal of cardiovascular electrophysiology 13.5 (2002): 502-512.

[3] Burattini, Laura, Wojciech Zareba, and Arthur J. Moss. "Correlation Method for Detection of Transient T Wave Alternans in Digital Holter ECG Recordings." Annals of Non-invasive Electro cardiology 4.4 (1999): 416-424.

[4] Nearing, Bruce D., and Richard L. Verrier. "Modified moving average analysis of T-wave alternans to predict ventricular fibrillation with high accuracy." Journal of Applied Physiology 92.2 (2002): 541-549.

[5] Monasterio, Violeta, Pablo Laguna, and Juan Pablo Martnez. "Multilead analysis of T-wave alternans in the ECG using principal component analysis." Biomedical Engineering, IEEE Transactions on 56.7 (2009): 1880-1890.

[6] Goovaerts, Griet, et al. "Tensor-based Detection of T Wave Alternans in Multilead ECG Signals." Proc. of the 41st annual computing in cardiology (2014).

[7] Laurent Sorber, Marc Van Barel and Lieven De Lathauwer. Tensorlab v2.0, Available online, January 2014. URL: http://www.tensorlab.net/.

[8] Burattini, L., and C. Giuliani. "T-wave frequency content evaluation in healthy subjects and patients affected by myocardial infarction." Signal Processing: New Research: 79-93.

[9] Martnez, Juan Pablo, et al. "A wavelet-based ECG delineator: evaluation on standard databases." Biomedical Engineering, IEEE Transactions on 51.4 (2004): 570-581.