USING THE PRINCIPAL COMPONENT ANALYSIS AS THE T WAVE ALTERNANS DETECTOR

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ABSTRACT

In this article a simulation study of T wave alternans (TWA) is tested in order to explore the usage and performance of Principal Component Analysis (PCA) for TWA detection. The aim is to explain electrical TWA and verify the usage properties of PCA.

1 INTRODUCTION

Microvolt-level electrical T wave alternans (TWA), defined as a consistent 2:l variation in the T wave morphology (Fig. 1.) has been recognized as a marker of electrical instability in a wide range of experimental and clinical situations, such as congenital long QT syndrome, myocardial ischemia and infarction and several other pathologic conditions. On the other hand [5], TWA is an arrhythmia risk marker to assess subtle changes in repolarization that has been introduced for arrhythmia and Sudden Cardiac Death (SCD) risk stratification. A lot of methods for TWA detection and evaluation were proposed. This article tries to test the PCA as a TWA detector.

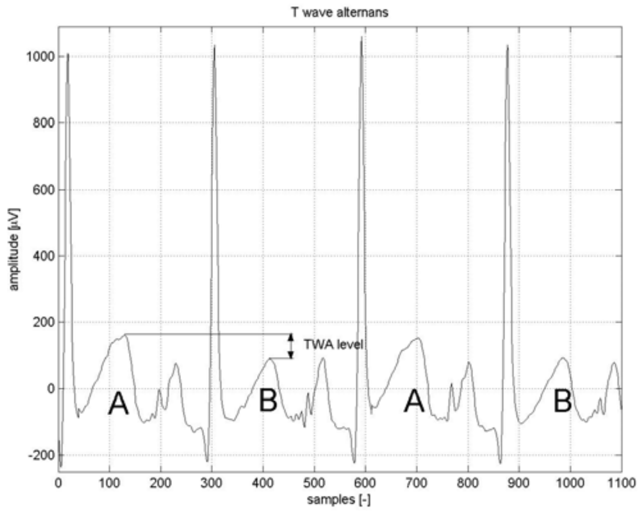

Fig. 1: *Introduction to TWA*

PCA is a well-known statistical method that is very similar to Karhunen-Loeve Transformation (KLT) [3, 4]. The KLT and PCA methods will be treated as if they were the same method throughout this article. These methods are orthogonal transform techniques that minimize the error between a signal and reduced linear combination of the basis functions. They have been widely used for data compression in signal and image processing applications. Further, PCA method will be discussed. The PCA makes it possible to see the sensible point of view on TWA. The PCA is theoretically optimal in terms of separating signal from noise. In the other words, PCA is a signal dependent transformation and it is the best possible characterization of the signal in a few dependent coefficients.

2 METHODS

In this study, the measured data from Department of Internal Medicine and Cardiology, University Hospital Brno were used. The ECG signals had been measured at the heart rate105 beats per minute with sampling frequency 3000 Hz. The sampling frequency was changed to 500Hz. The resolution is 2.29 μV/LSB. The second source of ECG signals was the well-known European ST-T Database [1] with resolution 4.55 μV/LSB.

Typically, 128 beats are analyzed. This number provides a reasonable compromise between the ability to reduce noise and the ability to track variations in the TWA level over time. The T wave alternance was simulated by addition or substraction Gauss-window to each second ST-T complex in range from the sixtieth to the eightieth beat. The TWA voltage level was chosen 60 μV.

2.1 PREPROCESSING

- *ORS detection*: FIR-filter based detector [2] was used.
- The next step was a *suppression of zero baseline fluctuation*.
- *Segmentation of the ST-T complex*: First step of segmentation was selection of the abnormal beats. The criteria were the amplitude of QRS complex and RR interval, described in [2]. The abnormal beats were replaced by average values from the beats which were not nearest neighbors. The second step was selecting time intervals that were found at a distance from the QRS peak dependent on the RR interval [1].

2.2 TWA DETECTOR BASED ON THE PCA

First, the d-dimensional mean vector μ and $d \times d$ covariance matrix $\sum$ are computed for the full data set [3, 4]. Further, the eigenvectors and eigenvalues are computed and sorted according to the decreasing eigenvalue. Call these eigenvectors e_1 with eigenvalue λ_1, e_2 with eigenvalue λ_2, and so on, and choose the k eigenvectors having the largest eigenvalues. Often there will be just a few large eigenvalues, and this implies that k is the inherent dimensionality of the subspace governing the signal, while the remaining $d - k$ dimensions generally contain noise. Next it forms a $d \times k$ matrix A whose columns consist of the k eigenvectors. The representation of data by principal component consists of projecting the data onto the k-dimensional subspace according to

$$x' = F_1(x) = A^T(x - \mu). \tag{1}$$

The PCA is computed for every 128-beat set and almost all the energy of signal is concentrated in the first four components ($k = 4$).

3 RESULTS

The four largest eigenvalues, which are represented by appropriate eigenvectors, were selected. Call this data packages like principal components. Following figures show 3D time representation of the four principal components, which represent the temporary TWA in the time domain.

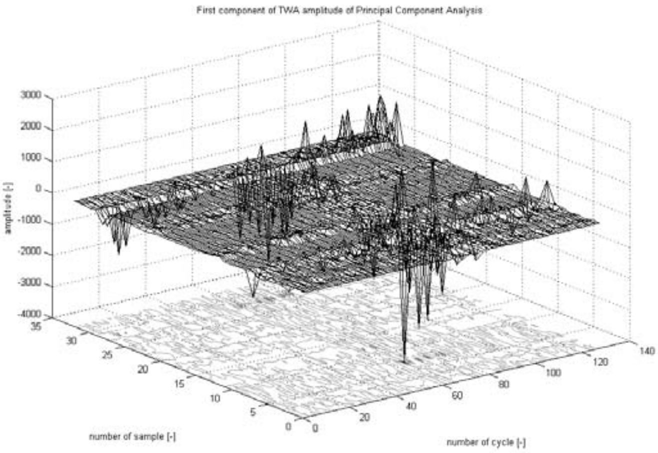

Fig. 2: *The First principal component*

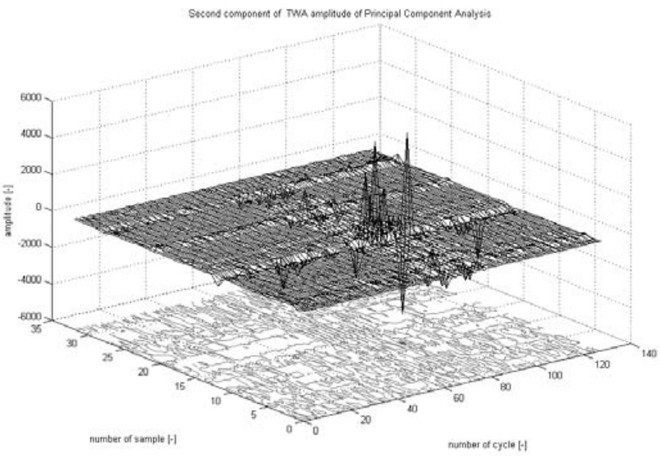

Fig. 3: *The Second principal component.*

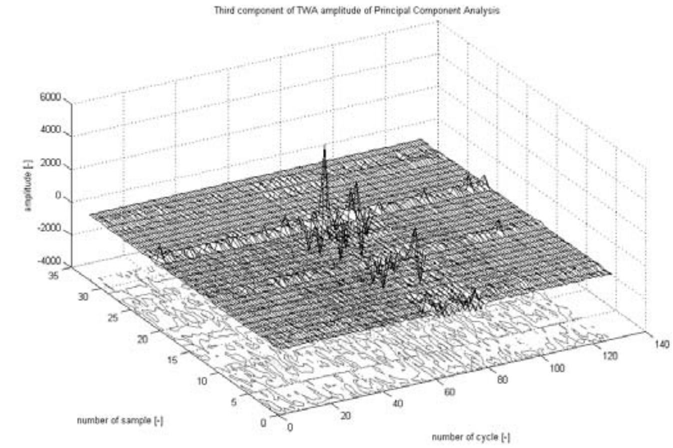

Fig. 4: *The Third principal component*

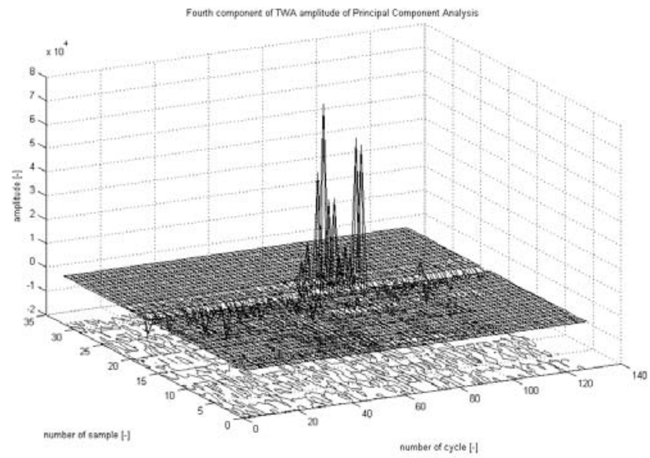

Fig. 5: *The Fourth principal component*

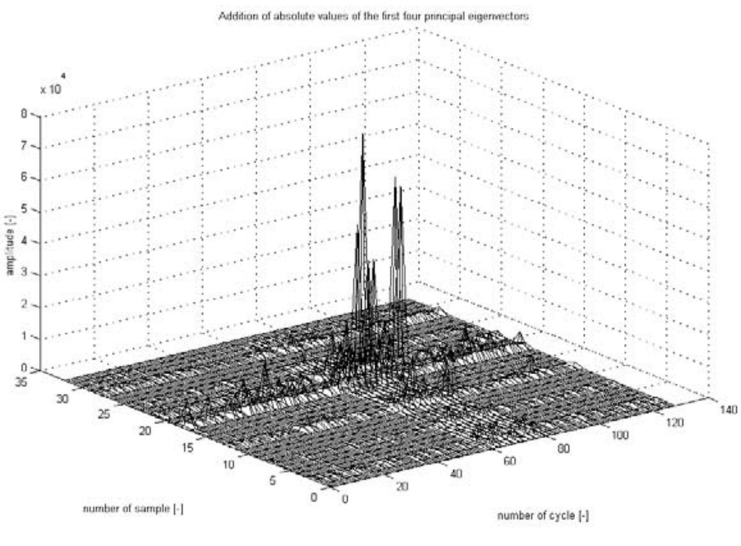

Fig. 6: *Addition of absolute values of the first four principal components*

The presence of the temporary TWA is shown in figures 2 – 5 as an increase contribution of PCA in the range from the sixtieth to the eightieth beat. Figure 6 provides a better view on TWA in 128 beats. It was made by addition of absolute values of the four TWA matrixes, which represent the first four principal components.

4 CONCLUSION

The linear PCA was implemented like the TWA detector. The PCA provides the possibility of dynamic tracking of T wave alternans like beat per beat. The time TWA mapping was found as more predicative and allows the complex view on TWA. In the time series representation of personal components, the TWA episodes appear as peaks as shown on fig. 6. The second possibility of using PCA for TWA detection was the extraction of representative vectors for the ST-T segments. The first principal component and the second one represent the dominant low-frequency component of the ST-T segment. The ratio between the second and the first eigenvalue represents the complexity of the repolarization segment [6]. The third, the fourth and the fifth component contain more high-frequencies.

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