Hybrid Detector for the T Wave Alternans Challenge

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Abstract

In the work presented here we propose an extended approach for the TWA modeling and detection based on a previous method presented in CinC07. To this aim, the ECG amplitude modulation and the baseline wander in the ST-T segment are approximated by a scaling factor applied to the T wave added to a constant. Thanks to this simplification, the proposed global model of each ST-T segment is constituted by the scaled T wave, an offset and the shape of the alternans. In addition to the modeling we also introduce a method to address the problem of the estimation of the T wave, the offset and the alternans shape and their respective coefficients. Thus, a model-based detector can be derived such as the generalized likelihood ratio test. Through this detection scheme, the orthogonality of the models is addressed and solved by imposing some constraints. The application of these constraints is driven by a student-t test output applied to the estimated parameters but also on the energy of the reconstructed T waves. An alternative detector based on a Principal Component Analysis is also proposed. Here again the presence of a baseline residual is accounted in the analysis. Since the last stage of the latter detector utilizes a student-t the selection of an optimal threshold is avoided. These detectors and alternans wave estimators are applied to the data set proposed by the CinC Challenge. It is shown that when applied on even short duration alternans it produces positive results. It is also shown that under the scope of the challenge the T waves segmentation plays an important role.

1. Introduction

It is well known that the event called T wave alternans (TWA) is a marker of cardiac instability and high risk of sudden death. Recently, index of presence of such event are used to decide whether a device has to be implanted. This phenomenon is observable with high rate of internal pacing, during coronary angioplasty intervention or when patients perform graded and maximal exercise test. The latter experiment does not need surgery and is a good candidate for TWA investigation. Unfortunately, because of the body motion observable during the exercise and an increasing tidal volume due to the effort, it exists a large modulation of the ECG signal added to a baseline wander larger than during resting conditions. Note that the ECG amplitude modulation and the baseline are also present in classical TWA records. It exists very few studies linking the TWA analysis performance to these sources of artifacts [1].

The CinC challenge propose a large variety of TWA episodes including a large number of simulated TWA with different magnitudes of the alternans waves. These simulated records are mostly affected by amplitude modulation and QT changes due to the varying heart rate. Since the ground truth is unknown for the remaining records, a global average of the entries from all participants forms the reference.

In [3] a detector based on the GLRT approach has been proposed to account for modulation and baseline artifacts. It has been named hybrid because in addition to the GLRT the computation of the modelling error used a student-t test applied to the scaling and offset parameters. It will be shown in the sequel that the test can be extended to a third parameter that is the energy of the reconstructed signal. This extension is supposed to alleviate the artificial description of the alternans by using the scaling and offset parameters.

Following the same idea that the observations model should take into account the recording artifacts, a second detector is proposed. It makes use of the singular vectors from the SVD of all the T wave segments. In that case, it is expected that the alternans wave participates to the overall variance and thus is contained in the singular vectors corresponding to the highest singular values. Unlike the first detector, this approach will get rid off the threshold selection pitfall by using a t-test of the projection coefficients. As it will be shown, the projection vectors will provide three coefficients that will be tested. The sensitivity will be maximized by accepting the detection if at least one of the three tests is positive.

To conclude the paper, some results from the challenge database are provided. It will be shown that the T waves segmentation strategy alters significantly the performances of the detectors. Segmentations based on the Bazett correction, the position of the T wave apex, the T wave offset location have been chosen as available strategies. It shows that the performance of any TWA detector and estimator not only relies on the model itself but also on the preprocessing.

2. Methods

In [3] the model that defines the N samples $\mathbf{x}_i$ as the observed i'th T has been proposed such as:

$$\mathbf{x}_i = \alpha_i(\mathbf{T} + a(-1)^i\mathbf{v}) + \beta_i \mathbb{1} \quad (1)$$

where $\mathbf{T}$, $\mathbf{v}$, α_i, β_i stand for the T wave, the alternans wave, a magnitude coefficient, the offset, respectively. The vector $\mathbb{1}$ will correspond to the unit vector. The binary value 0 or 1 for the a variable will permit us to distinguish or detect the episodes of TWA. This model accounts for a baseline component that is assumed to be constant in the T wave interval. The magnitude coefficient represents the modulation of the ECG signal during the recording.

Assuming a sliding window of length L, the segmented T wave will be grouped with L consecutive $\mathbf{x}_i$ ($i = 1 \dots L$). The presentation of the method can be simplified considering only one group, i.e. one window. The GLRT distinguishes the two hypotheses applied to the model (1): $H_0 : a = 0$ and $H_1 : a = 1$.

As shown in [3], the derivation of the GLRT should involve the computation of the estimated $\mathbf{T}$ by using the sample mean $\hat{\mathbf{T}} = 1/L \sum_{i=1}^{i=L} \mathbf{x}_i$. The estimation of $\mathbf{v}$ is more tedious and need the computation of the alternated sample mean $\tilde{\mathbf{x}} = 1/L \sum_{i=1}^{i=L} (-1)^i \mathbf{x}_i$. Residual $\mathbf{T}$ and $\mathbb{1}$ in $\tilde{\mathbf{x}}$ can be reduced applying:

$$\hat{\mathbf{v}} = (\mathbf{I} - [\hat{\mathbf{T}}\ \mathbb{1}][\hat{\mathbf{T}}\ \mathbb{1}]^{\#})\tilde{\mathbf{x}} \quad (2)$$

where $^{\#}$ stands for the pseudo-inverse and $\mathbf{I}$ the identity matrix. Once $\mathbf{T}$ and $\mathbf{V}$ have been estimated, the parametric models, that will be implied in the detection scheme, will be:

$$H_0 \quad : \quad \mathbf{x}_i = [\hat{\mathbf{T}}\ \mathbb{1}]\boldsymbol{\theta}_\mathbf{i} = \mathbf{M_0}\boldsymbol{\theta}_\mathbf{i} \quad (3)$$

$$H_1 \quad : \quad \mathbf{x}_i = [\hat{\mathbf{T}} + (-1)^i\hat{\mathbf{v}}\ \mathbb{1}]\boldsymbol{\theta}_\mathbf{i} = \mathbf{M_1}\boldsymbol{\theta}_\mathbf{i} \quad (4)$$

with $\boldsymbol{\theta} = [\alpha_i\ \ \beta_i]^T$. The non-orthogonality of the two models has been solved in [3] by using the constrains $\sum_{i=1}^{L}(-1)^i\alpha_i = 0$ and $\sum_{i=1}^{L}(-1)^i\beta_i = 0$ in H_0. Thus, the estimation of the parameters vector in H_0 is performed by using a constrained least square approach [3].

$$\begin{cases} \hat{\boldsymbol{\theta}}_1, \dots, \hat{\boldsymbol{\theta}}_L = \arg\min \sum_{i=1}^{L} \|\mathbf{x}_i - \mathbf{M}_0\boldsymbol{\theta}_i\|^2 \\ \text{subj } \sum_{i=1}^{L}(-1)^i\alpha_i = 0; \sum_{i=1}^{L}(-1)^i\beta_i = 0 \end{cases} \quad (5)$$

Prior to apply the constrains, a t-test has been applied to the two unconstrained parameters α_i and β_i. If positive ($p < 0.01$), the corresponding constrain on α_i and/or β_i in (5) is applied. In addition to this test applied separately to α_i and β_i, a third test can be applied to the estimated observation set $\hat{\mathbf{x}}_i = \mathbf{M}_0\hat{\boldsymbol{\theta}}_i$, where $\hat{\boldsymbol{\theta}}_i$ is the unconstrained estimated vector. Both constrains in (5) will be applied if the energy of the estimated observation passes successfully the t-test. Although evidence of optimality is not given here, this additional test reduces the effect of sharing the alternans information within the two parameters thus reducing the detection performance.

When the data in the sliding window produce a positive detection, its corresponding alternans wave (TWA) can be computed using the estimated parameters from the models [3].

One major drawback of such detector is the correct selection of the detection threshold γ. Since the output of the GLRT is a function of the TWA magnitude and the departures from the real observations regards the model, to set a correct threshold for a large variety of records is tedious. We propose in the following an alternative approach that get rid off this setting and still accounts for baseline residual.

The derivation of the second detector is based on the observation model:

$$\mathbf{x}_i \quad = \quad (\mathbf{v}_1\ \mathbf{v}_2\ \mathbb{1})\,\boldsymbol{\theta}_i + \mathbf{b}_i = \mathbf{M}_r\boldsymbol{\theta}_i + \mathbf{b}_i \quad (6)$$

with $\mathbb{1}$ the unit vector. Note that while the noise is added in (6) to be consistent with [4], it also has been taken into account in the previous detector. This expression can be compared to (1) where $\mathbf{v}_1$ and $\mathbf{v}_2$ play the role of $\mathbf{T}$ and $\mathbf{v}$ respectively. In real case, $\mathbf{M}_r^T\mathbf{M}_r$ is not equal to the unit matrix because there is no evidence that $\mathbf{v}_1$, $\mathbf{v}_2$ and $\mathbb{1}$ are mutually orthogonal. Assuming that the overall variance of the observations is due to the scaled T waves, the presence of the alternans waves and the offsets, an SVD applied to the matrix of the observation $\mathbf{X} = [\mathbf{x}_1\ \dots\ \mathbf{x}_J]$ should produce singular vectors related to $\mathbf{T}$ and $\mathbf{v}$.

We consider here the subspace $\langle\mathbf{K}\rangle$ corresponding to the reduced-rank least square approximation of the subspace $\langle\mathbf{M}_r\rangle$ imposing the partition $\mathbf{K} = [\mathbf{K}_a\ \mathbf{A}]$, with$\mathbf{K}_a$ a full-rank matrix and $\mathbf{A}$ a rank q matrix constituted by known vectors. As proven in [4], the least square approximation of the rank p subspace that best describe $\langle\mathbf{X}\rangle$ will correspond to the subspace that span the vectors in $\mathbf{U}$ associated to the $p - q$ highest singular values in $\mathbf{S}$, such that $(\mathbf{I} - \mathbf{A}\mathbf{A}^{\#})\mathbf{X} = \mathbf{U}\mathbf{S}\mathbf{V}^T$, appended to the vectors in $\mathbf{A}$. In the text, the symbol $^{\#}$ will stand for the pseudo-inverse. Since vector $\mathbb{1}$ is supposed to model the offset due to the residual baseline, the matrix $\mathbf{A}$ will contain only $\mathbb{1}$. The matrix $\mathbf{K}_a$ will be constituted by the vectors in $\mathbf{U}$ associated to the two highest singular values in $\mathbf{S}$, namely $\mathbf{u}_1$ and

$\mathbf{u}_2$. Thus the observation model can be approximated as:

$$\mathbf{x}_i \quad \approx \quad (\mathbf{u}_1 \; \mathbf{u}_2 \; \mathbb{1})\, \boldsymbol{\theta}_i + \mathbf{b}_i = \mathbf{K}\boldsymbol{\theta}_i + \mathbf{b}_i \qquad (7)$$

Thanks to the properties of $\mathbf{K}$, each vector $\boldsymbol{\theta}_i$ is estimated in the least square sense by :

$$\hat{\boldsymbol{\theta}}_i \quad = \quad \mathbf{K}^T \mathbf{x}_i \qquad (8)$$

Once all vectors $\boldsymbol{\theta}$ are estimated, the detection of the alternans episodes is performed by using a t-test on each component of the vectors. In order to account for the variation of the TWA presence, the t-test is applied on L length sliding window and not on the entire data. For a given a significance value, the selection of the detection threshold is straightforward. The vector of parameters is 3-dimensional, producing three detector outputs, one for each component. The sensitivity of the detector is maximized by concluding that a TWA is present when at least one detector output is positive. It should be noted that the number of vectors in $\mathbf{K}$ has been voluntarily reduced in order to avoid the sharing of the TWA information on a large number of component that could lead to a lack of sensitivity.

The alternans wave can be estimated using the estimated observation $\hat{\mathbf{x}}_i = \mathbf{K}\hat{\boldsymbol{\theta}}_i$ processed by the alternated average $\hat{\mathbf{v}} = 1/L \sum_{i=1}^{i=L} (-1)^i \hat{\mathbf{x}}_i$. In order to be consistent with the detector results, the alternans wave estimation is only computed on the window corresponding to a positive detection.

3. Results

The two presented detectors added to the classical GLRT given in [2] are applied to simulated data from [3] and from the CinC 2008 Challenge. In the former case, the parameters of the simulation are fully known unlike the latter where the magnitude of the TWA is only given. The data set from [3] is constituted by T waves already perfectly segmented that differs from the second where the entire 12-leads ECG is given.

In the first simulated data set, a 500mV T wave constituted the vectors $\mathbf{x}_i$ with a 16mV alternans waves. The scaling factors $\boldsymbol{\alpha}_i$ and offsets $\boldsymbol{\beta}$ have been chosen as in [3]. The first alternans wave is a large gaussian-like shape that appears within the index range [20-40]. The second alternans wave is a narrow gaussian-like shape that appears within the index range [80-100]. From the example in fig. (1), it is clear that while the GLRT detector ($L = 16$) proposed here exhibits good performances compared to the classical one, the difficulty in choosing the best threshold is not alleviated. The SVD-based detector proposed here as an alternative have been also applied to the same data set. Here again, results are in agreement with the simulation since at least one t-test is positive in a correct index interval. Apart from the detection, the TWA estimation is

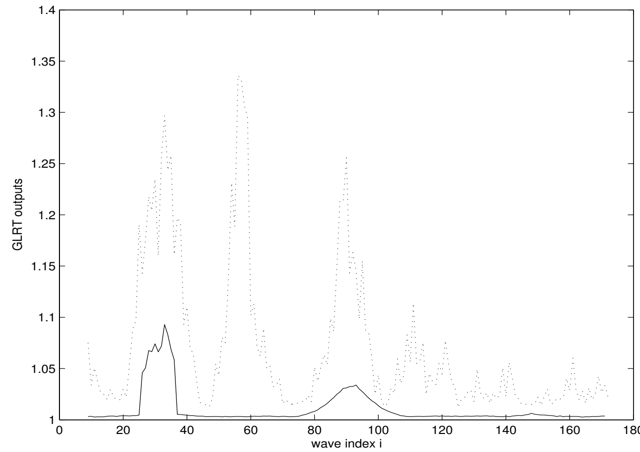

Figure 1. The outputs of the GLRT detector proposed in this paper (solid line) and the reference GLRT detector (dotted line)

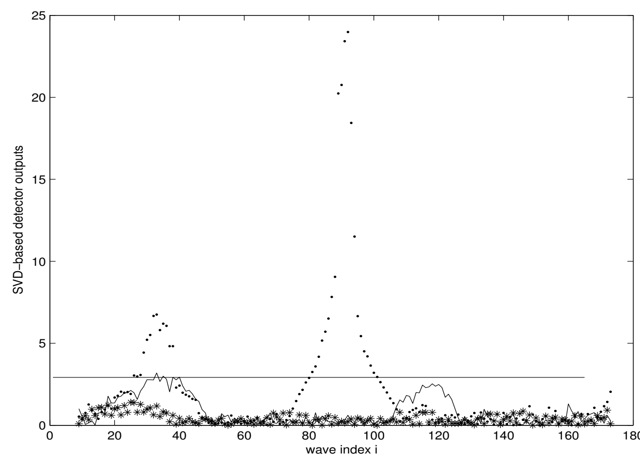

Figure 2. The three outputs of the SVD-based detector. The t-test results are given for the three parameters related to $\mathbf{u}_1$ (solid line), $\mathbf{u}_2$ (dots), $\mathbb{1}$ (stars). The horizontal line placed at the value 2.92 corresponds to $p = 0.01$ with $L = 16$

also of interest. On this example, the maximal TWA magnitude of detected episodes is 10.7mV, 19.2mV, 14.5mV for the new GLRT detector, the reference GLRT detector, the SVD-based detector, respectively. The next results illustrate how the T wave segmentation alters the detection performances. To this aim three techniques have been applied: a constant position window, a variable window corrected by using the well known Bazett formula, a window centered on the apex of each T wave. The record 91 from the challenge database has been chosen. This record being a simulated one, the TWA has been added with a maximal magnitude of 60mV on the lead V3. In fig. (3) and (4) results from the two GLRT detectors are plotted where it is

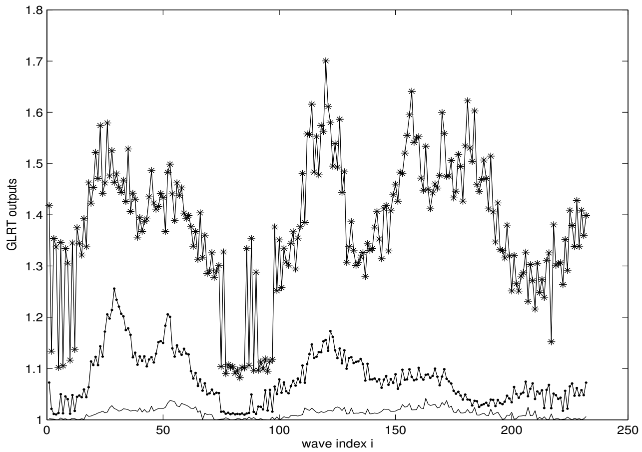

Figure 3. Outputs of the GLRT detector presented here for the three segmentations: constant position window (solid line), Bazett correction (dot point), aligned on the apex (star point)

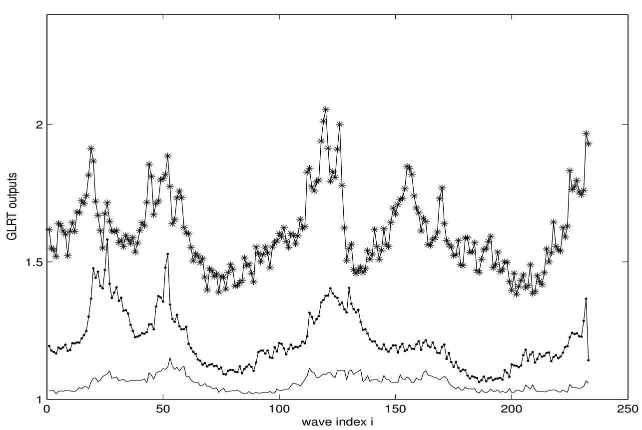

Figure 4. Outputs of the reference GLRT detector for the three segmentations: constant position window (solid line), Bazett correction (dot point), aligned on the apex (star point)

clear that best results are obtained using the third segmentation. In fig. (5), the SVD-based detector is applied on the third segmentation because for the others the behavior is the same than in fig. (3) and (4). Surprisingly they all estimate the maximal TWA magnitude around 22mV whereas the simulated value is 60mV. In spite of the fact that the data are simulated, one could conclude that an adapted segmentation is needed to improve the detection.

4. Discussion and conclusions

The inclusion of artifacts such as the modulation and offset due to the baseline is rarely accounted in the model

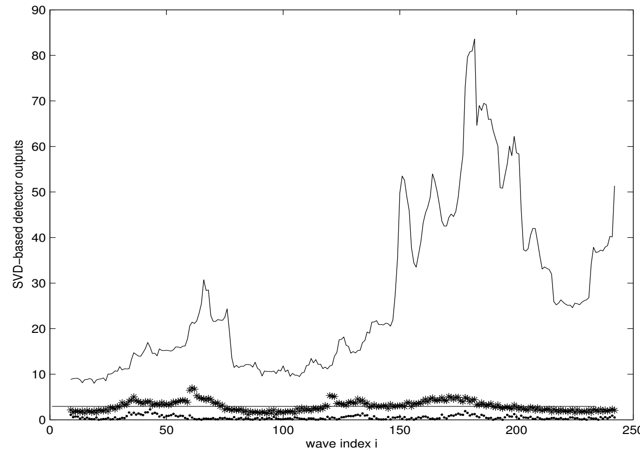

Figure 5. The three outputs of the SVD-based detector for segmentation based on the apex location

of TWA observations. We have attempted to introduce this idea since CinC 2007 by proposing an extension of the so-called GLRT detector. The problem of the non-orthogonality of the models under the two hypotheses have been solved by using constrains in the estimation process. We have presented here a refinement in the application of these constrains. While this family of detector is efficient the pitfall of the threshold setting is not really alleviated. Thus we have oriented the work toward detectors based on SVD that includes the presence of offset, where the final step makes use of a t-test. The selection of the detection threshold is thus straightforward. Few results from the CinC 2008 Challenge database show that the segmentation of the T waves should be done with care.

References

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