Analysis of the T Wave Alternans Phenomenon with ECG Amplitude Modulation and Baseline Wander

O Meste[1], D Janusek[2], R Maniewski[2]

[1]Lab I3S, Universite de Nice-Sophia Antipolis, France
[2]Institute of Biocybernetics and Biomedical Engineering, Warsaw, Poland

Abstract

In the work presented here we propose a new approach for the TWA modelling and detection. For 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. Note that since these components are unknown, the problem of the estimation is ill posed. In addition to the modelling 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. Since the application of the constraints is driven by a student-t test, this hybrid detector will take advantage of both approaches.

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].

After proposing a model that fits these observation, a GLRT-based detector is proposed accounting for the hypothesis of TWA presence. Finally, results from the application of the proposed method to realistic simulated records exhibit better performances compared to classical approaches. Applied to real data, we show that the TWA phenomenon can be detected using our approach. In that case, the detector proposed here doesn't outperform the reference one [3] because the recording conditions are almost ideal, i.e. weakly modulated T wave and no baseline wander.

2. Methods

After a QRS detection stage, the segmentation of the T waves is performed on the ECG. Some refinement can be added by using a correction of the T wave onset that takes into account the previous R-R interval. For the sake of clarity the noise will not be accounted in the model even it will be considered in simulation. The proposed method accounts for the model that defines the N samples $\mathbf{x}_i$ as the observed i'th T wave 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. 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. The modulation is due to the varying distance separating the heart from the sensors. This effect is magnified as the volume of the lungs increases.

This model differs from the usually considered one, that is:

$$\mathbf{x}_i = \mathbf{T} + a(-1)^i\mathbf{v} \quad (2)$$

where a lack of generalization is clear. It is well adapted when a preprocessing is applied. In particular baseline removal is generally recognized as an important processing step that is beneficial to TWA detection [2]. However some methods that exhibits robustness regards the baseline as been proposed [1] but not in a modelling approach. The simplified model (2) is certainly efficient under resting condition or anesthesia but probably not for dynamic condition that corresponds to exercise or Holter ECG.

The methods developed here belongs to the classical detection framework. The review paper [3] presents well accepted methods in this field compared to the Generalized likelihood ratio test (GLRT). The design of this detector is addressed with an observation noise considered either as gaussian or laplacian, with a variance σ . The latter will produce the Laplacian Likelihood Ratio [4]. 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):

$$H_0 : a = 0 \tag{3}$$

$$H_1 : a = 1 \tag{4}$$

We will assume here a zero mean gaussian noise uncorrelated both in time and from a segment to another. Thus, the mathematical calculation of the GLRT will be similar to those given in [3] and extended as:

$$GLRT = \frac{p(\mathbf{X}; \hat{\mathbf{v}}, \hat{\mathbf{T}}, \hat{\boldsymbol{\alpha}}_1, \hat{\boldsymbol{\beta}}_1, \hat{\sigma}_1, H_1)}{p(\mathbf{X}; \hat{\mathbf{T}}, \hat{\boldsymbol{\alpha}}_0, \hat{\boldsymbol{\beta}}_0, \hat{\sigma}_0, H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \tag{5}$$

where the matrix $\mathbf{X}$ contains the $\mathbf{x}_i$'s.

The derivation of the GLRT should involve maximum likelihood estimation of the parameters (noted $\hat{}$ in (5)). Several remarks can be done concerning this estimation and the good agreement between the proposed model (1) and the GLRT. First, from (1) it is obvious that the model is not identifiable since the product $\alpha_i \mathbf{T}$ is not unique. Second, if $\mathbf{v}$ tends to $\lambda \mathbf{T}$, the two hypotheses can not be distinguished. This means that making a detection possible needs to constrain the model by adding a priori regards the parameters.

We assume here that α_i and β_i are randomly distributed with means equal to 1 and 0, respectively. Thus, the estimation of $\mathbf{T}$ is achieved by computing 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 $\tilde{\mathbf{x}} = 1/L \sum_{i=1}^{i=L} (-1)^i \mathbf{x}_i$. Depending on the variance of α_i and β_i a residual $\mathbf{T}$ and $\mathbb{1}$ will remain in $\tilde{\mathbf{x}}$ that will reduce the detection performance and the results interpretation. Since it is expected that $\tilde{\mathbf{x}}$ contains $\mathbf{T}$, $\mathbb{1}$ and $\mathbf{v}$ a second processing is applied in order to get rid off the residual components. This processing is computed by:

$$\hat{\mathbf{v}} = (\mathbf{I} - [\hat{\mathbf{T}}\ \mathbb{1}][\hat{\mathbf{T}}\ \mathbb{1}]^{\#})\tilde{\mathbf{x}} \tag{6}$$

where $^{\#}$ stands for the pseudo-inverse and $\mathbf{I}$ the identity matrix. This estimation implies that alternans wave is orthogonal to the mean T wave and is zero mean. In case of weak modulation and baseline, the vector $\tilde{\mathbf{x}}$ could be considered as an estimated $\mathbf{v}$ reducing the computation cost.

Once $\mathbf{T}$ and $\mathbf{V}$ have been estimated the parametric models, that will be implied in the detection scheme, will be:

$$H_0 \quad : \quad \mathbf{x}_i = [\hat{\mathbf{T}}\ \mathbb{1}]\boldsymbol{\theta}_\mathbf{i} = \mathbf{M_0}\boldsymbol{\theta}_\mathbf{i} \tag{7}$$

$$H_1 \quad : \quad \mathbf{x}_i = [\hat{\mathbf{T}} + (-1)^i \hat{\mathbf{v}}\ \mathbb{1}]\boldsymbol{\theta}_\mathbf{i} = \mathbf{M_1}\boldsymbol{\theta}_\mathbf{i} \tag{8}$$

with $\boldsymbol{\theta} = [\alpha_i\ \beta_i]^T$. As previously mentioned, formally the two hypotheses cannot be distinguished using these two models since model 1 is included in model 0. One solution consists in imposing to the parameters α_i and β_i (for $i = 1 \dots L$) the constraints $\sum_{i=1}^{L}(-1)^i \alpha_i = 0$ and $\sum_{i=1}^{L}(-1)^i \beta_i = 0$. That constraints prevent the parameters to exhibit a behavior corresponding to an alternans wave that should be only supported by the hypothesis H_1. This property is relevant when the alternans wave is close to the estimated T wave. In other words, this correspond to the case where the alternans wave and the estimated T wave are almost colinear. Since accounting these constraints in the estimation procedure is meaningless when the TWA is absent, a student's t-test [5] can be applied to the parameters estimated in a first step. Applied to the two set of parameters, a positive test will lead to include the constraints in the estimation. This will be performed by using a constrained least square approach:

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

The classical approach to solving this constrained optimization problem will be the method of Lagrange multipliers.

Finally, the values σ_0 and σ_1 are estimated up to a common factor such as:

$$\hat{\sigma}_0 = \sum_{i=1}^{L} \|(\mathbf{I} - \mathbf{M}_0 \mathbf{M}_0^{\#})\mathbf{x}_i\|^2 \tag{9}$$

$$\hat{\sigma}_1 = \sum_{i=1}^{L} \|(\mathbf{I} - \mathbf{M}_1 \mathbf{M}_1^{\#})\mathbf{x}_i\|^2 \tag{10}$$

Thus, the GLRT is completely defined by using the equation:

$$GLRT = \frac{\hat{\sigma}_0}{\hat{\sigma}_1} \tag{11}$$

It should be noted that this ratio is not raised to the power LN in order to reduce its dynamic.

In addition to this detection method, the estimation of the alternans component (TWA) can be computed using the estimated parameters from the models. Assuming that the number of segmented T wave is greater than L, the k'th estimated TWA from the k'th set of L observation is given by:

$$\widehat{TWA}_k = \frac{1}{L}\sum_{i=1}^{L}(\mathbf{M}_1\mathbf{M}_1^{\#} - \mathbf{M}_0\mathbf{M}_0^{\#})(-1)^{i+k}\mathbf{x}_i \quad (12)$$

In the next section, the method will be compared to the reference one [3]. One major difference between the two methods is that the reference one needs a preprocessing step in order to get rid off the presence of the T wave. The proposed preprocessing is to compute the difference $\mathbf{y}_i = \mathbf{x}_i - \mathbf{x}_{i-1}$ and to detect the TWA by using this detrended new set of data. Assuming that the model (1) is valid since any baseline wander cancellation and demodulation does not perform perfectly, the output of the preprocessing step will be:

$$\mathbf{y}_i = (\alpha_i - \alpha_{i-1})\mathbf{T} + (\alpha_i + \alpha_{i-1})(-1)^i\mathbf{v} + (\beta_i - \beta_{i-1})\mathbb{1}$$

It is clear that if the α_i's and β_i's are constant, the new set will exhibit the TWA only. If not, since the two coefficients are one and zero mean respectively, the preprocessing will reduce the influence of the T wave and enhance the TWA component. A version of the proposed method can also be derived when the $\mathbf{y}_i$'s are used instead of the $\mathbf{x}_i$'s

3. Results

Results on one simulation and one real case will be given here. From a real T wave a series of segmented observations is simulated including a random offset, a random scaling (see fig. 1) and two kind of gaussian shaped alternans wave. In fig. 2, we can see that the first is similar in width and position to the T wave unlike the second that is shifted and more narrow. Alternans of the first and second wave starts respectively at beat index 20 and 80, with a duration of 20 beats for both types. In order to check for the robustness of the method, the second wave has been added to the T wave without the alternans effect at beat index 140, with a duration of 20 beats.

A constant window with $L = 16$ has been used for the proposed detector and for the reference one [3]. For the application of the reference method, the segments have been preprocessed as previously mentioned. For the application of the constraints, a t-value of 2.94 has been chosen for a significance level equal to 0.01. Results are given in fig. 3, where it can be seen that the proposed method detects correctly the occurence of the two alternans waves, unlike the reference detector. In addition to this result, the performance of the two detectors are compared in fig. 4 where the amplitude modulation and the offset are weak, in that case 10 times lower than for the first simulation.

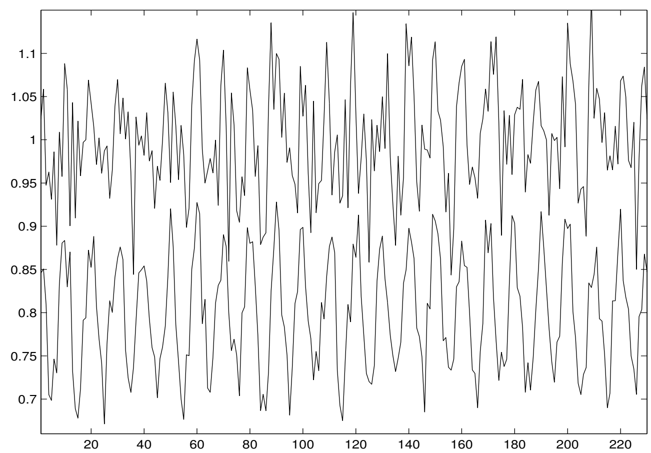

Figure 1. The α_i (top) and β_i (displayed with an offset of 0.8, bottom) coefficients computed for the simulation.

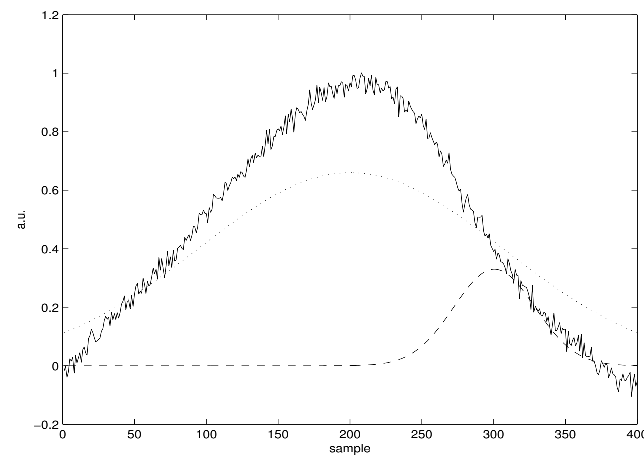

Figure 2. Signals involved in the simulation. A noisy T wave (solid line), the first alternans wave magnified by 10 (dotted line), the second alternans wave magnified by 10 (dashed line)

As an illustration, the next result will concern the application of the GLRT-based detector to a patient undergoing angioplasty. Data are from the STAFF III database with a location of the balloon inflation corresponding to the left anterior descending artery. On this example, the occlusion time corresponds to the 178'th beat. In fig. 5, the presence of the TWA is clearly visible using both methods. It shows that at least when the TWA is very clear, the proposed method performs as well as the reference one.

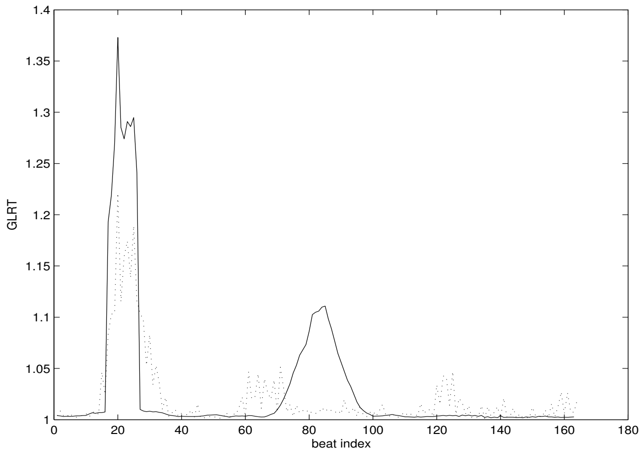

Figure 3. The two outputs of the GLRT based detectors. Comparison between the detector presented in this paper (solid line) and the reference one (dotted line)

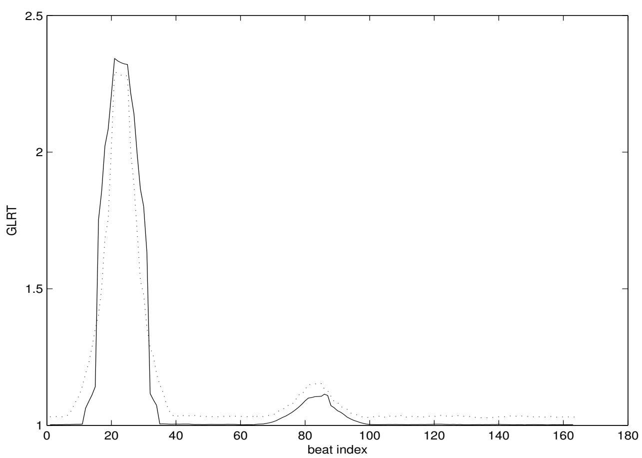

Figure 4. The two outputs of the GLRT based detectors for an amplitude modulation and offset divided by 10. Comparison between the detector presented in this paper (solid line) and the reference one (dotted line)

4. Discussion and conclusions

All the referenced methods designed for the TWA detection and estimation are based on a simple model that does not take into account the possible baseline residual and amplitude modulation of the whole ECG. Under exercise conditions or during Holter recordings these two disturbances are actually encountered. We have proposed a detector based on the GLRT approach that directly includes in the model of the observations a scaling factor and an offset added to the alternans wave. The derivation of the detector has been developed using constraints that transform the detector into a hybrid one. Comparison to the reference detector that is the GLRT shows that the proposed detector

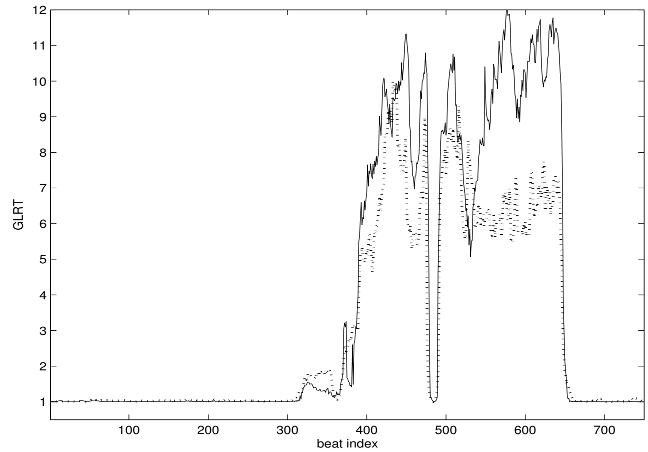

Figure 5. The two outputs of the GLRT based detectors for the real case. Comparison between the detector presented in this paper (solid line) and the reference one (dotted line)

is well adapted to bad recording conditions. Under ideal conditions, methods are equivalent. Compared to method that considers Laplacian noise [3], the GLRT framework allows the adaptation of the presented method to this assumption as well.

References

[1] Burattini L, Zareba W, Burattini R. The effect of Baseline Wandering in Automatic T-wave Alternans Detection from Holter Recordings. Comput. Cardiol., 2006; 33:257–260.

[2] Burattini L. Electrocardiographic T-wave Alternans detection and significance, Doctoral thesis, University of Rochester, 1998.

[3] Martinez J P, Olmos S. Methodological Principles of T Wave Alternans Analysis: A Unified Framework. IEEE Trans. Biomed. Eng., 2005;52:599-613.

[4] Martinez J P, Olmos S, Laguna P. T Wave Alternans and Acute Ischemia in Patients Undergoing Angioplasty. Comput. Cardiol., 2002;29:569-572.

[5] Srikanth T, Lin D, Kanaan N, Gu H, Presence of T Wave Alternans in the Statistical Context–A New Approach to Low Amplitude Alternans Measurement, Comput. Cardiol., 2002;29:681–684.

Address for correspondence:

O. MESTE
Laboratoire I3S UNSA-CNRS 2000,
route des lucioles Les Algorithmes - bt. Euclide B BP.121 06903
Sophia Antipolis - Cedex France
meste@i3s.unice.fr