Nonlinear Detection of T-Wave Alternans

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Abstract

Automatic detection of T-wave alternans (TWA) is the PhysioNet/Computer in Cardiology Challenge 2008. The method presented in this paper is based on combination of linear and rank statistics.

1. Introduction

T-wave alternans (TWA) is usually manifested as variation of amplitude or morphology of the T-wave in every other beat. [1,2] However, there are variety of descriptions and quantification methods for the phenomenon. [1-5] The PhysioNet/Computer in Cardiology Challenge 2008 provides a challenge for developing a fully automatic system for TWA detection. [6] The challenge leaves several open issues for algorithm design: handling of the abnormal and noisy beats, the noise estimates, the changes in TWA phase and amplitude, and the selection of the optimal position of the TWA-detection window.

In this work, an algorithm for detecting TWA is presented. The algorithm is designed for fully automatic analysis and tested with the PhysioNet/Computer in Cardiology Challenge 2008 database.

2. Methods

The challenge database consists of 72 12-lead, 12 3-lead and 16 2-lead ECG recordings. All signals are provided with 500 Hz sampling rate and 16-bit digital resolution. The signals come from variety of sources and there are notable differences in signal quality. The signals were randomized and are accompanied with the QRS detections. [7]

Proposed signal analysis method for detecting the TWA is divided here into two phases: The pre-processing phase includes steps for general signal improvement and waveform detection, and the TWA algorithm phase contains the signal processing that is specific to the TWA detection and quantification. All the signal-processing methods are implemented in custom-made software.

Preprocessing:

1. 50/60 Hz notch filtering.
2. Triggering (for the challenge records, given annotations were used)
3. Baseline correction: Baseline wandering is estimated with a third order spline fitted to successive TP intervals. The spline is then subtracted from the ECG.
4. Detection of T-wave apex: First, the maximum deviation from the baseline after the QRS complex is defined as the T-apex. [8] Next, a slope is fitted to the RTapex (time from R-peak to T-apex) – RR scatter plot. Finally, T-apex is redefined as the peak of the second order polynomial fitted around the time-instant defined by the RR-time and the RTapex/RR-slope.
5. Correction of the signal amplitude variation: First, the QRS-amplitude time series is formed by determining the QRS amplitudes for each beat. Next, a third order spline is fitted to the time series. The spline is then normalized to average amplitude of one, and the ECG signal is rescaled by dividing it with the normalized spline.
6. Rejection of the bad beats: Beats are rejected, if the RR-interval differs more than 25 % from the previous one, or if the signal noise exceeds 0.3 mV or signal-to-noise ratio (SNR) 8. The noise is defined as the minimum standard deviation (STD) of the signal during 50 ms long time interval before the QRS-complex. The SNR is defined as the maximum STD of the 70 ms long interval during the QRS divided by the noise value.

TWA algorithm:

1. Normalization of the signal amplitude: ECG amplitude is normalized by setting an average sum of the T-wave amplitude and the QRS amplitude to one. The normalizing results unitless TWA estimates and it was skipped when microvolt TWA estimates were defined.
2. TWA-windowing: The ECG signal from 120 ms before to 120 ms after the T-apex is resampled. The resampling is performed with a 150 ms long sinc-function and it is done in order to ensure the sampling-independent time matching of the T-wave windows.

3. Sample series: Two every-other-beat sample series are formulated for each sample (j) in TWA-window and for every 24-beat-long interval without any rejected beats (n). The signal from 24 ms before to 24 after the beat is first detrended. Then, two 12-sample long every-other-beat series are formulated:

$$serie_{kjn} = \begin{Bmatrix} [-12,-8,-6\ldots,8,10], k=1 \\ [-11,-9,-7\ldots,9,11], k=2 \end{Bmatrix}$$

4. *Difference of median values:*

$$MedDiff_{jn} = \left| Median(serie_{1jn}) - Median(serie_{2jn}) \right|$$

5. *Average median* absolute deviation:

$$MAD_{jn} = \left(\sum_{k=1}^{2} Median\left(\left| Median(serie_{kjn}) - serie(i)_{kjn} \right| \right) \right) \Big/ 2$$

6. *TWA* and *ratio sample estimates*:

$$SampleEst_{jn}: \begin{matrix} TWA_{jn} = MedDiff_{jn} - MAD_{jn} \\ ratio_{jn} = MedDiff_{jn} / MAD_{jn} \end{matrix}$$

7. *Beat estimate*: the highest average of 8 successive *sample estimates*:

$$BeatEst_n = \underset{i \in [1,116]}{Max} \left(\sum_{j=i}^{i+8} SampleEst_{jn} \right) \Big/ 8$$

8. *Channel estimate*: The average of the highest 50 to 75 % of the *beat estimates:*

$$ChEst = \left(\sum_{i=1/2*nok}^{3/4*nok} Sort(BeatEst)(i) \right) \Big/ (1/4 * nok),$$

where *nok* is the number of beats and *sort* an operator for sorting samples in descending order.

9. Measurement estimate: The average of the top 1/3 of the channel estimates:

$$\begin{matrix} TWA \\ ratio \end{matrix} = \left(\sum_{i=2/3*nch}^{nch} Sort(ChEst)(i) \right) \Big/ (1/3 * nch),$$

where *nch* is the number of leads, and 1/3**nch* is one for 2- and 3-lead measurements and four for 12-lead measurements.

10. *TWA measurement estimate* is used as the TWA estimate for all the measurement whose ratio measurement estimates exceeded three. If the ratio is below three, TWA estimate is set to zero.

3. Results

TWA was analysed from all the challenge records with and without signal amplitude scaling (section 1.in TWA algorithm). The TWA and the ratio estimates are shown in figure 1. The TWA was detected in 22/100 of the records. These records are listed in table 1. Two of the records didn't have 24 beat long sinus rhythms (24 succeeding non rejected beats), and the algorithm set TWA for those to zero.

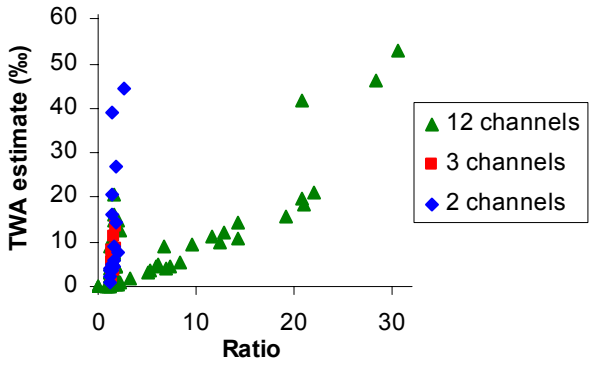

Figure 1. TWA measurement estimate is shown in Y- and ratio in X-axis. The records are plotted with different symbols depending the number of channels in the record. It can be seen that the population has too branches: one with lower noise content and thus higher ratio values and one with clearly lower ratio values.

Table 1. The records with positive TWA test. The TWA estimate values are given in unitless normalized values (‰) and in microvolt (μV) values.

Record	TWA estimate		Ratio
	‰	μV	
twa29	52.78	27.35	30.50
twa13	46.00	40.80	28.30
twa34	41.49	39.21	20.73
twa79	21.05	20.35	21.93
twa09	19.80	12.59	20.88
twa97	18.52	9.88	20.99
twa91	15.85	10.64	19.23
twa17	14.18	7.47	14.32
twa72	12.09	10.97	12.76
twa01	11.36	7.75	11.52
twa06	10.74	6.92	14.35
twa50	9.73	9.36	12.44
twa73	9.28	8.45	9.49
twa33	8.75	4.89	6.63
twa21	5.47	3.48	8.44
twa98	5.14	2.91	6.13
twa82	4.68	4.36	5.94
twa70	4.56	3.00	7.30
twa51	4.12	4.53	6.92
twa15	3.42	2.18	5.22
twa67	3.00	1.93	5.07
twa64	1.82	1.75	3.27

The results didn't take part in the official competition and aren't included in competition median [6], but they were tested against the median. The scores were 0.645 for the normalized TWA and 0.644 for the microvolt TWA.

4. Discussion and conclusions

The algorithm presented in this work was designed to base on combination of simple non-linear and linear mathematics. Most of the previously reported methods, the frequency domain methods [3], the averaging methods [4] or the correlation methods [5], are based on linear mathematics, which leads to more easily interpretable results. The main benefits of non-linear mathematics and rank statistics are the better tolerance to non-Gaussian noise from missed or ectopic beats or from movement artefacts.

In pre-processing phase of the algorithm, special emphasis was given to the features that might create TWA-like alternation on signal: The T-apex detection variability between different peaks in bipolar or multiphasic T-waves, was approached in the 4th section of pre-processing, and the signal amplitude variation, caused by the breathing, was approached in the 5th section. The rejection of the non-sinus rhythms, especially bigeminy, was approached by RR-time variation based rejection (6th section). However, if the beat and/or rhythm annotation is available, it is certainly worth using instead of simple heart rate based rejection.

The TWA algorithm contains many distinct phases and several selectable constants for window lengths, limits etc. Most phases are necessary for algorithm to work, but the resampling in TWA-windowing isn't mandatory; it can be replaced with the closest sample values. However, in our studies the MAD-values, which are used as noise estimates (5th section in TWA algorithm), were increased over 10 percent in the best quality records, when resampling was dropped out. With noisier signals the effect was smaller, but it will most probably be more significant with lower sampling rates that are typical e.g. of Holter recordings.

One of the strengths of the developed algorithm is the possibility to detect short-term TWA; thus the algorithm has good tolerance for TWA phase shifts. This tolerance was achieved in the first phase of the algorithm (6th. and 7th sections). For balancing that and since the algorithm was aimed to be noise--tolerant the second phase (sections 8th and 9th) were added. Unfortunately, the counter-side of the noise-tolerance is the decreased sensitivity to TWA. The sensitivity to TWA was further reduced with the last part of the algorithm (10th section). It was added, instead of just using the channel with highest TWA estimate to balance the comparisons between 2, 3 and 12-lead measurements. However, since no TWA was detected in 2- or 3-lead records, in practice the only effect from the addition to the challenge results was diminished TWA sensitivity for 12-lead measurements.

We investigated also the location of the maximally alternating parts during the STT segment. There was no clear similarity between the cases with moderate TWA sample estimate values. However, in the records with the highest TWA the alternating voltage correlated heavily with the signal amplitude. On the other hand, the closer inspection on these records showed that they were most likely simulated; so further analysis didn't look meaningful. If it is cleared that all the recordings are real, then the issue is worth further inspection.

Limitations: In order to prevent the "training effect" the author tried to be careful and not to inspect the competition data before finalizing the algorithm. However, the data--set was once reanalysed and the algorithm altered to the current state after the first test with altogether 3 different analysing set-ups: The rejection of the bad beats was modified and the algorithm was simplified by dropping out some phases, which had very little effect to final results. Thee use of T-wave end for defining the TWA-window length and the triggering with custom-made algorithm were skipped. In addition, the ratio limit for TWA detection, which was originally automatically set, was manually altered to three. The automatic setting had problems on handling the sections with noise but not rejected beats, which resulted too high detection limit for hole set. The selected value 3 was based on some analogy with alternans ratio limit in commonly used TWA algorithms, e.g. [3], and it divides nicely the scatter plot in Figure 1.

Finally the results were computed three times with slightly different settings on algorithm: Once without the QRS or signal amplitude scaling (4th and 6th section of the pre-processing), once without signal amplitude scaling (6th section) and once with the complete algorithm. The results from the first and second computation were so similar that the first was dropped out from the results. The other two results are both presented in Table 1, as the second run resulted values in micro volts, and the complete algorithm resulted unitless values.

Plans: The published competition data set is planned to be used for algorithm fine-tuning. Especially the window lengths and the noise cancellation parts in the TWA algorithm are planned to be re-examined. After fine-tuning, the algorithm is going to be tested with several clinical and research data sets in cooperation with the Helsinki University Central Hospital.

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