Sensitivity of T-Wave Alternans Identification Algorithms to Residual Physiological Noise Affecting the ECG after Preprocessing

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Abstract

To address the issue as to how and at what extent physiological noise that survives preprocessing affects TWA detection and quantification, a test was performed here on the fast-Fourier-transform spectral method (FFTSM), modified-moving-average method (MMAM), and adaptive-match-filter method (AMFM). These methods were applied to four synthetic ECG tracings respectively affected by no TWA, stationary TWA, and time-varying TWA. Absence and presence of physiological noise (from the MIT-BIH noise stress test database from the PhysioNet web site) were considered. Our results indicate that the FFTSM is robust to noise but has an intrinsic limitation in the precision of time-varying TWA quantification. Noise significantly affects TWA detection and quantification by the MMAM, while the AMFM offers a good compromise between robustness to noise and ability to identify both stationary and time varying TWA.

1. Introduction

Electrical T-wave alternans (TWA), defined as every-other-beat fluctuation in the repolarization morphology, is a harbinger of malignant ventricular arrhythmias and sudden cardiac death [1-6]. In recent years, several automatic methods for TWA identification have been proposed. Among these, the fast-Fourier-transform-spectral method [5] and the modified moving-average-method [6] are the most commonly used because implemented in commercial machines (CH2000 and Heartwave, Cambridge Heart Inc., Bedford, MA; and CASE-8000, GE Medical Systems, Milwaukee, WI, respectively). Both these techniques require a conditioning of the ECG for noise reduction before being applied for TWA analysis. Such preprocessing stage is not required by a more recent TWA detection method proposed by ourselves [7,8], which uses a heart-rate adaptive match-filter to filter out every ECG component, including those related to noise, but the TWA typical one.

Since physiological noise always affects ECG recordings and is usually not perfectly removed by the preprocessing stage, aim of the present study was to compare the ability of the FFTSM, MMAM and AMFM to correctly detect and quantify TWA in noisy conditions. To this aim, these competing methods were applied to four synthetic ECG tracings, respectively affected by no TWA, stationary TWA, and time-varying TWA characterized by either smoothed-step or sinusoidal trend. These synthetic ECGs were considered in the absence of noise or after adding recordings of either electrodes motion noise, or muscular noise, or baseline wanderings.

2. Methods

2.1. Simulated data

Four basic ECG tracings (Fig.1), were synthesized as a 128-fold repetition of a single noiseless beat extracted from a real ECG (sample frequency = 200 Hz, RR interval= 0.75 s): 1) NO_TWA tracing, characterized by the absence of TWA, 2) S_TWA tracing, characterized by a stationary TWA having an amplitude of 20 μV, 3) STEP_TWA tracing, with TWA amplitude varying from 20 μV to 0 μV according to a smoothed (24 beats transition) step pattern, and 4) SIN_TWA tracing, with TWA amplitude varying from 20 μV to 0 μV following a sinusoidal pattern, with 40 beats period. All tracings were characterized by a uniform profile of TWA, according to which all samples of the T wave alternate by the same quantity.

ECG corruption was obtained by adding portions (96 s) of electrode motion noise (EL1 and EL2), muscle noise (MUS1 and MUS2) and baseline wandering (BAS1 and BAS2) recordings taken from the MIT-BIH noise stress test database, available at the PhysioNet web site (http://www. physionet. org/ physiobank). These real noise signals were scaled so that their maximum amplitudes (difference between maximum and minimum) were either 0 μV (i.e. no noise), or 50 μV, or 100 μV. The time course of all six kinds of physiological noise, throughout the analyzed period, is shown in Fig. 2 for the 100 μV normalization case.

2.2. TWA Detection methods

Fast-Fourier-transform spectral method (FFTSM). According to this technique [5], the digital ECG complexes are aligned, and the power spectrum of each sample in the T-wave window is estimated. Then, the spectral amplitude of the cumulative spectrum at 0.5 cpb is compared to a specifically computed spectral noise level to decide the presence of TWA, and is eventually used to estimate the TWA amplitude.

Modified-moving-average method (MMAM). This approach [6] consists of a time-domain procedure according to which even and odd beats are recursively averaged. Some nonlinear constraints are applied to limit the effect of local artefacts. TWA amplitude is computed as the maximal absolute difference, in the T wave segment, between modified-moving-averaged even and odd beats.

Adaptive-match-filter method (AMFM). According to this technique [7,8], TWA amplitude is estimated by measuring the amplitude of a sinusoidal TWA signal obtained from filtering the digital ECG tracing with a match-filter centred at the TWA fundamental frequency which is, by definition, equal to a half heart rate.

2.3. Statistics

The ability of each method to quantify TWA amplitude was evaluated by computing the root mean square error (RMSE; μV) over the ECG length (128 beats).

$$\text{RMSE} = \sqrt{\frac{\sum(\text{estimated TWA} - \text{simulated TWA})^2}{128}} \quad (1)$$

3. Results

In the absence of noise, the outputs of the FFTSM, MMAM and AMFM were affected by no error when applied to NO_TWA and S_TWA tracings. Instead, the methods provided RMSE of 9 μV, 3 μV and 2 μV, respectively, when applied to STEP_TWA, and 7 μV, 7 μV and 3 μV, respectively, when applied to SIN_TWA.

Application to ECG tracings affected by 50 μV and 100 μV noise yielded the results reported in Table 1. The FFTSM was able to accurately recognize the absence of TWA in NO_TWA tracings, and the presence of stationary TWA in S_TWA tracings, with RMSE equal to zero in the six cases affected by 50 μV noise, and up to 1 μV in the six cases affected by 100 μV noise. RMSE increased in the presence of time-varying TWA with values of 9 μV for STEP_TWA, and 7 μV for SIN_TWA, irrespectively of noise maximum amplitude. Noise significantly affected the MMAM behavior in that this algorithm detected false-positive TWA from all twelve noisy NO_TWA tracings. Accuracy of TWA quantification from S_TWA, STEP_TWA, and SIN_TWA decreased with increasing noise amplitude (RMSE=2÷9 μV for 50 μV noise, and RMSE=4÷12 μV for 100 μV noise). Noise also affected the AMFM output.

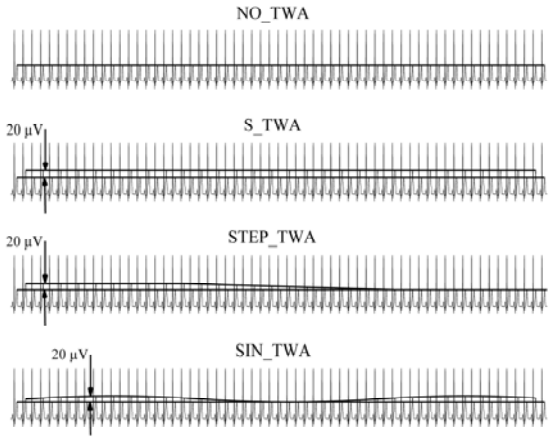

Figure 1. Simulated ECG tracings affected by no TWA (NO_TWA), stationary TWA (S_TWA), smoothed step time-varying TWA (STEP_TWA), and sinusoidal time-varying TWA (SIN_TWA).

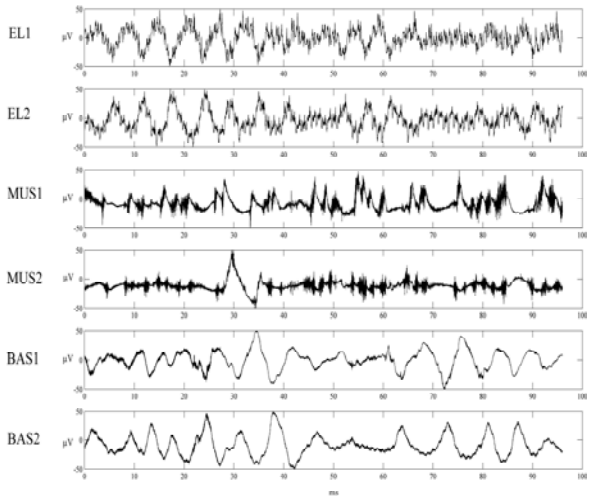

Figure 2. Portion (96 s) of 100 μV electrode motion noise (EL1 and EL2), muscle noise (MUS1 and MUS2) and baseline wanderings (BAS1 and BAS2) recordings.

Table 1. Root mean square errors (RMSE; μV) obtained by application of FFTSM, MMAM, and AMFM to NO_TWA, S_TWA, STEP_TWA and SIN_TWA tracings affected by six (EL1, EL2, MUS1, MUS2, BAS1, BAS2) different kinds of noise, having 50 μV and 100 μV maximum amplitude.

		$RMSE_{EL1}$ (μV)	$RMSE_{EL2}$ (μV)	$RMSE_{MUS1}$ (μV)	$RMSE_{MUS2}$ (μV)	$RMSE_{BAS1}$ (μV)	$RMSE_{BAS2}$ (μV)
50 μV							
	NO_TWA						
	FFTSM	0	0	0	0	0	0
	MMAM	7	5	4	3	5	4
	AMFM	0	0	0	0	0	0
	S_TWA						
	FFTSM	0	0	0	0	0	0
	MMAM	3	4	4	2	4	2
	AMFM	2	1	2	1	1	1
	STEP_TWA						
	FFTSM	9	9	9	9	9	9
	MMAM	8	7	7	5	6	6
	AMFM	2	2	2	2	2	2
	SIN_TWA						
	FFTSM	7	7	7	7	7	7
	MMAM	9	8	8	8	8	8
	AMFM	3	3	4	3	3	3
100 μV							
	NO_TWA						
	FFTSM	0	0	0	0	0	0
	MMAM	13	7	7	4	10	9
	AMFM	0	0	3	0	0	0
	S_TWA						
	FFTSM	1	0	1	0	0	0
	MMAM	4	5	6	4	10	5
	AMFM	5	3	4	2	2	1
	STEP_TWA						
	FFTSM	9	9	9	9	9	9
	MMAM	10	10	11	8	12	8
	AMFM	3	3	3	2	2	2
	SIN_TWA						
	FFTSM	7	7	7	7	7	7
	MMAM	9	8	10	9	11	9
	AMFM	5	3	4	3	4	3

Indeed, this method detected one false-positive TWA case from the NO_TWA tracing corrupted by 100 μV MUS1 noise, and quantified TWA from S_TWA, STEP_TWA and SIN_TWA with errors ranging from 1 to 5 μV.

4. Discussion and conclusion

This simulation study was designed to compare the reliability of the FFTSM, the MMAM and the AMFM, in the process of identifying TWA in clinical ECG recordings affected by physiological noise surviving the preprocessing stage. To this aim, a set of four ECG tracings, namely NO_TWA, S_TWA, STEP_TWA and SIN_TWA, was considered. NO_TWA ideally represents the tracing of a healthy subject not affected by TWA. S_TWA is also an ideal case of TWA, since the time-varying nature of TWA is well known [8-12]. TWA stationarity is a reality simplification, originally hypothesized by the FFTSM for a correct use of the Fourier transformation. Clinical ECG recordings with visible TWA show that this phenomenon may have an on-

off or a cyclic trend [13]. Consequently, at microvolt levels, these two kinds of TWA are represented by STEP_TWA, and SIN_TWA, respectively. In all considered tracings affected by TWA, a uniform alternans was hypothesized over the T wave [13] to allow a comparative analysis, since all three identification methods have identical ability to correctly quantify TWA in this condition (see Results and [13]).

Because of its underlying hypothesis of stationarity, the FFTSM correctly recognized the absence of TWA in NO_TWA and the presence of 20 μV stationary TWA in S_TWA, whereas it provided significant TWA estimation RMSE (7÷9 μV over a 0÷20 μV TWA-amplitude range) when analyzing STEP_TWA and SIN_TWA, independently of noise amplitudes. FFTSM robustness to noise derives from the fact that its algorithms takes into account only the 0.5 cpb component (i.e. TWA frequency) of the cumulative spectrum, and no the other components which may pertain to noise.

When applied to noisy NO_TWA tracings, the MMAM provided false-positive TWA with estimated amplitudes ranging from 3 to 7 μV in the presence of 50 μV noise and from 4 to 13 μV in the presence of 100 μV noise. These results confirm the tendency of this algorithm to ascribe to TWA other kinds of noise-driven or physiological variability [13-14]. Moreover, the MMAM ability to correctly estimate TWA decreases with increasing TWA time-variability and with increasing noise amplitude (RMSE up to 12 μV over a 0÷20 μV TWA-amplitude range).

Due to its ability to filter out every ECG component other than TWA, the AMFM keeps the RMSE within 5 μV even in the presence of 100 μV noise. Such a high noise level caused an accidental false-positive TWA case of 3 μV amplitude (NO_TWA, MUS1). Eventually, the AMFM appears particularly suitable to identify both stationary and time-varying TWA [13].

In conclusion, our results indicate that the FFTSM is robust to noise but has an intrinsic limitation in the precision of time-varying TWA quantification. Noise significantly affects TWA detection and quantification by the MMAM, while the AMFM offers a good compromise between robustness to noise and ability to identify both stationary and time-varying TWA.

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