Advanced Detection of ST Segment Episodes in 24-Hour Ambulatory ECG Data by Automated Tracking of Transient ST Segment Reference Level

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Abstract

Using the Long-Term ST Database, we developed and evaluated an advanced algorithm for automated detection of transient ST segment episodes in "real-world" 24-hour ambulatory data. To successfully detect transient ST change episodes, the algorithm automatically tracks the time-varying ST segment reference level due to clinically not important non-ischemic causes and subtracts it from the ST segment level. Evaluating of the algorithm using reference annotations of the protocol B of the database yielded gross ST episode detection sensitivity and positive predictivity of approximately 75%.

1. Introduction

Ambulatory electrocardiogram (ECG) data typically shows wide and significant ($>50\mu$V) changes in amplitude of ST segment level due to: slow drifts, changes of electrical axis of the heart (postural changes), changes in ventricular conduction, heart-rate related changes and ischemia. In the last few years, a number of recognition techniques to automatically detect transient ischemic ST segment episodes in ambulatory ECG (AECG) records were developed. Systems developed are limited in their ability to deal with significant non-ischemic ST segment changes, or do not deal with them at all. To successfully detect transient ischemic and heart-rate related ST episodes, the time-varying ST segment level due to other clinically not important non-ischemic causes defines the time-varying ST segment reference level, which has to be tracked. Newly developed Long-Term ST Database (LTST DB) [1] (see also: http://www.physionet.org/physiobank/database/ltstdb/) contains 24-hour AECG records and expert human annotations marking: time-varying ST segment reference level, significant transient ischemic and heart-rate related ST segment episodes annotated in each ECG lead separately, and significant sudden changes of ST segment level due to axis shifts and conduction changes. We present an algorithm for advanced automated detection of transient ST segment episodes in 24-hour AECG data by automated tracking of transient ST segment reference level.

2. Methods

The LTST DB contains 86 two- and three-channel AECG records of 80 patients sampled at 250 samples per second per channel. Annotating of the LTST DB was based on considerable preprocessing phase [1] yielding time series of a number of diagnostic and morphologic features (including QRS complex and ST segment Karhunen-Loève transform (KLT) coefficients) which helped expert human annotators during annotating. The developed algorithm incorporates a traditional time-domain and the KLT approach. Input data to the algorithm were (besides raw ECG data): ARISTOTLE's (arrhythmia detector [2]) fiducial points of normal and non-noisy heart beats (those which passed preprocessing phase of the database) of the records of the LTST DB, and time series of QRS complex and ST segment KLT coefficients. All these data are available to users in the annotation and utility files of the LTST DB. The main features of the algorithm developed include: sequential average beats construction, automatic searching for the positions of the isoelectric level and J points, construction of the *ST level function* in each ECG lead, automatic tracking of the time-varying ST segment reference level in each lead to form the *ST reference function*, construction of the *ST deviation function* in each lead as algebraic difference between the ST level and ST reference function, combining the absolute ST deviation functions from the leads into the *ST detection function*, and automatic detecting of transient ST change episodes.

Sequential average heart beats are computed over a 16-second window surrounding each normal and non-noisy heart beat. In these average beats, the algorithm searches for the isoelectric level in the P-Q interval and for the J point. For the position of the isoelectric level, the algorithm searches backwards (in each ECG lead) from the ARISTOTLE's fiducial point (FP) for up to 60ms for a sample in which the slope of the waveform equals zero or changes sign. This may be the end of P-Q interval, the R or the Q peak. The algorithm then searches backwards to the point FP-108ms for the "flattest" 5-sample segment of the waveform. For this purpose, the mean absolute deviation of each segment from its own mean value is calculated, and the segment with the minimal absolute deviation is considered the flattest, or, the P-Q interval. The middle

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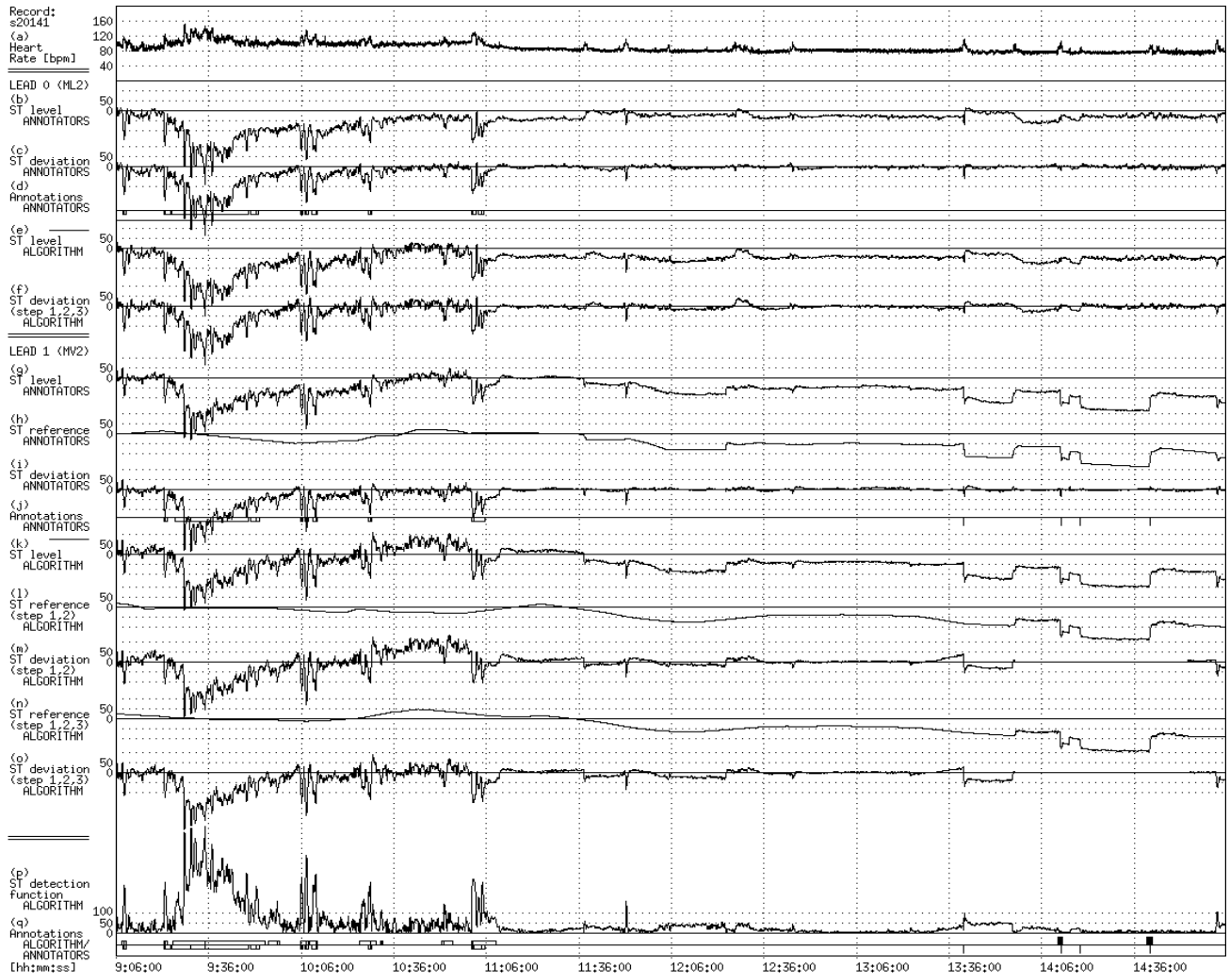

Figure 1. Heart rate, ST segment functions (units are in μV) and ST segment annotation streams of the record s20141 of the LTST DB. (a) Heart rate [bpm]; *Lead 0 (ML2):* (b,c) ST level and ST deviation function, (d) ST annotation stream derived by expert annotators (10 heart-rate related ST episodes), (e,f) ST level and ST deviation function derived by the algorithm; *Lead 1 (MV2):* (g,h,i) ST level, ST reference and ST deviation function, (j) ST annotation stream derived by expert annotators (8 heart-rate related ST episodes and four axis shifts), (k,l,m) ST level, and ST reference and ST deviation function after step 1 and 2 of the algorithm, (n,o) ST reference and ST deviation function after all three steps of the algorithm (see text); (p) ST detection function; (q) Combined ST change episode annotation stream (9 episodes) and reference axis shift annotations (4) by expert annotators (below the line), and ST change episodes (10) and axis shifts (2) detected by the algorithm (above); The ST change episodes are present in the first two hours, while the axis shifts in the last two.

sample of this segment defines the isoelectric reference point for the lead. The absolute deviations of the segments at each isoelectric reference point are summed over all leads, and that isoelectric reference point yielding minimal sum is the final isoelectric reference point for all leads. The isoelectric level is then defined in each lead as the mean of 5 surrounding signal samples. For the position of the J point, the algorithm searches forwards (in each ECG lead) from the FP for up to 32ms for a sample where the slope of the waveform equals zero or changes sign. This may be the R or the S peak. From this point, or from the FP if such a sample is not found, the algorithm searches forwards for up to 68ms for the part of the waveform which starts to "flatten". For this purpose, the algorithm calculates for each signal sample the absolute amplitude difference between the mean of three preceding signal samples and the mean of three trailing samples. The first one of the three consecutive signal samples for which this absolute amplitude difference is less than 10μV is considered as the sample at which the waveform starts to flatten, or, the J point. Then the position of the J points of the leads are compared and that being furthest from the FP is taken as

unique J reference point for all leads. The positions of the isoelectric level and J points of the average beats are used to construct the ST level function, $stlev(i,j)$, where i denotes the lead number and j denotes the beat number. A sample of the ST level function is defined as the ST segment amplitude measured in the average heart beat at the point J+80ms (the mean of 5 surrounding samples) if heart rate (HR) is less than 100 bpm (or J+72ms if 100≤HR<110, or J+64ms if 110≤HR<120, or J+60ms if HR≥120) from which the isoelectric level is subtracted. The ST level functions of the leads are then resampled (0.5 Hz) and smoothed with 7-point moving average filter. Fig. 1 shows heart rate, ST segment functions and ST segment annotation streams of the record s20141 of the LTST DB. The ST level functions derived by expert annotators are shown in Fig. 1.b and 1.g, while the algorithm's in 1.e and 1.k. The aggregate average error between the samples of the ST level functions derived by the expert annotators and those derived by the algorithm was 2.3μV (St.d.=9.9μV), 2.2μV (St.d.=9.4μV), and -0.6μV (St.d.=9.2μV), for the leads 0, 1, and 2 of the LTST DB, respectively.

The ST reference function is derived for each ECG lead in three steps: 1.) Estimation of the ST segment reference level trend due to slow drifts; 2.) Identification of sudden step changes in the ST level function due to axis shifts; 3.) Determination of the lead "orientation" (depressed or elevated ST segment episodes present) and updating the ST reference function.

In the first step, the algorithm estimates the time-varying local and global ST segment reference level trend, $lstref(i,k)$ and $gstref(i,k)$, respectively, where k is the sample number in the resampled functions, by applying the bank of two moving-average low-pass filters over 900 samples (30 minutes), h_1, and over 7200 samples (4 hours), h_2, to the ST level function. The ST reference function in this step is estimated following:

$$stref_{(1)}(i,k) = \begin{cases} gstref(i,k) & : \text{if} \\ \quad |gstref(i,k) - lstref(i,k)| > 50\mu\text{V} \\ lstref(i,k) & : \text{otherwise.} \end{cases}$$

In the second step, sudden step changes of the ST level function are searched for in each ECG lead in those intervals for which $|gstref(i,k) - lstref(i,k)| > 50\mu$V. For this purpose, the algorithm uses the ST level function and the Mahalanobis distance functions of the QRS complex and ST segment KLT coefficients. In each of these functions, the algorithm searches first for a flat segment of 108 samples (216 seconds) in length, which has to have its mean absolute deviation from its mean value less than $K_f = 10\mu$V for the ST level function, and less than $\Sigma_f = 0.33$ for both distance functions. Such a flat segment has to be followed by a step change, which is characterized by the moving average value over 36 samples (72 seconds) in length and has to change by at least $K_s = 50\mu$V for the ST level function, and $\Sigma_s = 0.5$ for both distance functions, within the next 72 samples (144 seconds). This step change has to be followed by another flat interval, defined as for the first flat interval. In the intervals surrounding each step change detected, the ST reference function is updated (Fig. 1.l) following:

$$stref_{(2)}(i,k) = \begin{cases} stlev(i,k) & : \text{if} \\ \quad |gstref(i,k) - stlev(i,k)| > 10\mu\text{V} \\ stref_{(1)}(i,k) & : \text{otherwise.} \end{cases}$$

The majority of leads of the LTST DB show only one type of ST segment episodes (elevations or depressions). The type determines the lead orientation. To determine the lead orientation, the ST deviation function, $stdev_{(2)}(i,k)$, is constructed as $stlev(i,k) - stref_{(2)}(i,k)$ (Fig. 1.m). A histogram of $stdev_{(2)}(i,k)$ is shown in Fig. 2. The samples corresponding to episodes of ST segment depressions cause higher values on the left side of the distribution. To determine the lead orientation, the algorithm calculates the absolute sum of differences between the samples of the $stdev_{(2)}(i,k)$ and the 50μV threshold (for those samples that exceed 50μV threshold) to obtain $psum(i)$, and the absolute sum of differences between the samples of the $stdev_{(2)}(i,k)$ and the -50μV threshold (for those samples that are less than -50μV threshold) to obtain $nsum(i)$. The lead orientation, $o(i)$, is defined as E (elevations) if $psum(i)$ is greater than $nsum(i)$ for more than 2500μV, D (depressions) if $nsum(i)$ is greater than $psum(i)$ for more than 2500μV, or U (undecided) otherwise. The ST reference function for the lead is then updated according to lead orientation,

$$stref_{(3)}(i,k) = \begin{cases} stref_{(2)}(i,k) : \text{if} \\ \quad (o(i) = \text{E} \wedge stdev_{(2)}(i,k) > 0\mu\text{V}) \\ \quad \vee (o(i) = \text{D} \wedge stdev_{(2)}(i,k) < 0\mu\text{V}) \\ \quad \vee (o(i) = \text{U} \wedge |stdev_{(2)}(i,k)| > 25\mu\text{V}) \\ stlev(i,k) \quad : \text{otherwise,} \end{cases}$$

and smoothed by the moving-average low-pass filter h_1 in the intervals being updated in this third step (Fig. 1.n). Compare this automatically derived ST reference function to that derived by expert annotators (Fig. 1.h). Then, the final ST deviation function for each ECG lead (Fig. 1.f, 1.o) is derived:

$$stdev_{(3)} = stlev(i,k) - stref_{(3)}(i,k).$$

Compare these functions to those derived by expert annotators (Fig. 1.c, 1.i).

The ST detection function is defined as the sum of the absolute ST deviation functions from the leads:

$$stdet(k) = \sum_{i=0}^{N-1} |stdev_{(3)}(i,k)|,$$

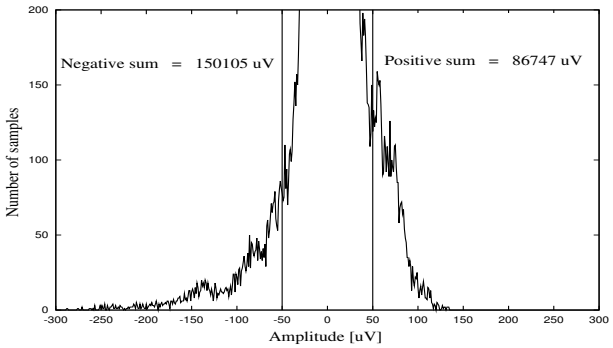

Figure 2. Histogram of the ST deviation function, $stdev_{(2)}(i,k)$, of the lead 1 of the record s20141 of the LTST DB. The lead "orientation" is D (depressions).

where N is the number of leads (Fig. 1.p). Constants of the algorithm so far were determined empirically. To detect ST change episodes, the algorithm follows criteria defining significant transient ST segment episodes [1] in the leads of the LTST DB, and employs them in the ST detection function. Three sets of reference ST episode annotations are available in the LTST DB. Protocol A includes: ST segment deviation $\geq 75\mu$V for at least 30 seconds; protocol B: $\geq 100\mu$V for at least 30 seconds; and protocol C: $\geq 100\mu$V for at least 60 seconds. Timing criteria were strictly kept together with two amplitude thresholds identifying the exact beginning, peak extrema and exact end of ST episodes (see [1]). The lower amplitude threshold of 50μV was kept, while the upper one, V_u, was adjusted for each set of reference ST episode annotations. The detector performance characteristic curve of gross ST episode detection sensitivity versus gross ST episode detection positive predictivity was employed for each set of the reference ST episode annotations to obtain the optimal V_u. The adjusting constraint was approximately equal sensitivity and positive predictivity. Optimization procedure yielded $V_u = 110\mu$V (protocol A), $V_u = 150\mu$V (B), and $V_u = 150\mu$V (C).

3. Results

The ischemic and heart-rate related ST segment episodes from the simultaneous ECG leads of the LTST DB were merged together in the sense of logical OR function into one single combined ST change annotation stream for each record. Merging yielded 1490 combined ST change episodes for the protocol A, 908 for the protocol B, and 663 for the protocol C. To assess the performance of the algorithm, we used performance measures described in [3]. Performance results are summarized in Table 1.

Protocol A	STE Se	STE +P	STD Se	STD +P
Gross	71.0% (65.4%)	71.3% (64.0%)	63.7% (58.2%)	60.8% (53.9%)
Average	71.7% (67.3%)	73.5% (68.3%)	67.6% (62.9%)	66.2% (60.9%)
Protocol B	**STE Se**	**STE +P**	**STD Se**	**STD +P**
Gross	74.9% (69.7%)	75.4% (66.6%)	65.1% (59.7%)	64.1% (57.0%)
Average	73.9% (68.0%)	76.9% (71.3%)	68.8% (63.3%)	68.7% (63.1%)
Protocol C	**STE Se**	**STE +P**	**STD Se**	**STD +P**
Gross	77.2% (71.7%)	80.3% (72.5%)	63.2% (57.0%)	66.3% (59.4%)
Average	71.8% (66.2%)	80.2% (74.5%)	67.4% (61.8%)	71.4% (65.7%)

Table 1. Report on performance of the algorithm using the LTST DB. *Legend:* STE - ST episode, STD - ST duration, Se - sensitivity, +P - positive predictivity. Bracketed are bootstrap statistics (lowest expected performance - 5% confidence limits on 10,000 trials).

4. Discussion and conclusions

We developed a new algorithm capable of tracking the time-varying ST segment reference level and detecting transient ST segment episodes. Tracking the ST segment reference level is crucial ability for the reliable ST segment episode detection, resulting in high sensitivity and positive predictivity. We hope that other algorithms will be developed (and existing ones improved) and evaluated using the LTST DB, so the performance of the algorithms could be compared. We plan further improvements of the algorithm by incorporating information of raw signal waveforms.

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