Automatic Detection of ST-T Complex Changes on the ECG Using Filtered RMS Difference Series: Application to Ambulatory Ischemia Monitoring

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***Abstract*—A new detector is presented which finds changes in the repolarization phase (ST-T complex) of the cardiac cycle. It operates by applying a detection algorithm to the filtered *root mean square* (rms) series of differences between the beat segment (ST segment or ST-T complex) and an average pattern segment. The detector has been validated using the European ST-T database, which contains ST-T complex episodes manually annotated by cardiologists, resulting in sensitivity/positive predictivity of 85/86%, and 85/76%, for ST segment deviations and ST-T complex changes, respectively. The proposed detector has a performance similar to those which have a more complicated structure. The detector has the advantage of finding both ST segment deviations and entire ST-T complex changes thereby providing a wider characterization of the potential ischemic events. A post-processing stage, based on a cross-correlation analysis for the episodes in the rms series, is presented. With this stage subclinical events with repetitive pattern were found in around 20% of the recordings and improved the performance to 90/85%, and 89/76%, for ST segment and ST-T complex changes, respectively.**

***Index Terms*—Automatic ischemia detection, ECG, ST-T complex changes, ST segment deviations.**

I. Introduction

ISCHEMIC heart disease constitutes one of the most common fatal diseases in the western hemisphere. Myocardial ischemia is caused by a lack of sufficient blood flow to the contractile cells and may lead to myocardial infarction with its severe sequellae of heart failure, arrhythmias, and death [1]. During the last years, ambulatory monitoring of the electrocardiographic (ECG) signal has become the noninvasive test most widely used for detecting cardiovascular diseases. Ischemic ECG changes typically precede the onset of anginal pain and, hence, these may be the only sign of "silent myocardial ischemia" [2]. Therefore, it is essential to develop methods that detect early changes in the ECG, possibly indicating the onset of an acute ischemic syndrome.

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Different ECG changes related to the evolution of ischemia have been described, including T wave amplitude changes, ST deviations and even alterations in the terminal portion of the QRS complex [3]. In different situations T wave changes could precede ST segment deviations during the ischemic process [3], [4] and, therefore, should be considered in monitoring systems. The use of global representations for the ST-T complex instead of using a single point from the ST segment better characterizes ischemic patterns [5], [6], and yields better identification of an occluded artery [7]. Unfortunately, commercial equipment usually considers a fraction of the whole repolarization period, i.e., the ST60 or ST80 point.

Different algorithms have been designed for analyzing the ST segment, either in the ECG signal [8], [9] or in the averaged ECG [10]–[18]. Several mathematical transforms have been applied to the ECG for ischemia detection: the discrete cosine transform (DCT) and the discrete Fourier transform (DFT) were used for classification of repolarization patterns [19], and the Karhunen–Loève transform (KLT) was used to detect changes in the ST segment [20] and the entire ST-T complex [5], [21]. Other techniques such as artificial neural networks [22]–[24] and fuzzy-logic [25] have been also proposed.

The *European ST-T database* [26] was developed with the objective to assess the quality of ambulatory ECG systems. It is composed of recordings with episodes of repolarization changes manually annotated by different cardiologists, consisting of ST segment and T wave changes. This database has recently been used to test different ST algorithms but the detection of T wave changes have not been explored yet.

We propose the design and validation of a system that detects changes either in the ST segment, or in the entire ST-T complex (including the T wave), thereby providing a wider characterization of ischemic events. Section II describes the different parts of the detector, the database for validation and the performance measures. A cross-correlation study between episodes is also included. The validation results are shown in Section III and are further discussed in Section IV.

II. Materials and Methods

A. European ST-T Database

The *European ST-T database* [26] consists of 90 double-channel 2-hour ECG recordings, extracted from Holter tapes (two-lead ECG's) that contain ST-T complex episodes annotated on an individual lead basis by cardiologists. The events are distributed in 368 episodes of ST segment

TABLE I
REFERENCE ANNOTATION SETS FOR ST SEGMENT AND ST-T COMPLEX INTERVALS, ORIGINALLY AT THE *EUROPEAN ST-T DATABASE*, AND AFTER LOGICAL *OR* COMBINATION (SEE TEXT FOR DETAILS)

	ST segment	**ST-T complex**
original	368	368 ST + 401 T
OR comb.	250	392

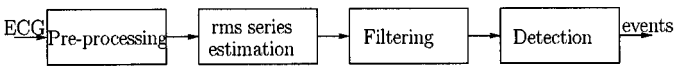


Fig. 1. Detector structure.

deviations and 401 of T wave changes. It is possible to combine the lead-by-lead annotations for each recording using a logical *OR* and the widest limits in time into a new lead-independent set (see Table I). For the study of the ST-T complex changes, a new annotation set was derived using the *OR* combination of ST segment and T wave episodes, and *OR* combination between leads. These two sets of 250 ST segment and 392 ST-T complex episodes were used for validation of the detector performance.

B. Detector Design

The proposed detector includes signal preprocessing, computation of the root mean square (rms) difference series, filtering, and a decision algorithm which finds the ischemic events, see Fig. 1.

The preprocessing consisted of QRS detection and normal beats selection according to the arrhythmia detector ARISTOTLE [27], baseline wander attenuation using cubic splines [28], and rejection of noisy beats [those with low signal-to-noise ratio (SNR) with respect to an exponentially averaged SNR or with differences in mean isoelectric level with respect to adjacent beats larger than 400 μV]. In order to avoid the influence of high frequency noise in the rms difference series (e.g., 50/60 Hz noise), the ECG was low-pass filtered using a linear phase FIR filter (cutoff frequency $f_c = 25$ Hz). Beat segmentation was done by selecting intervals of 50 and 300 ms for the ST segment and ST-T complex, respectively, beginning at a distance from the QRS fiducial point dependent on the RR interval. The onset of the intervals for the ith beat, b_i, is given by

$$b_i = 40 + 1.3 \cdot RR_i^{1/2} \qquad \text{(in milliseconds)}. \tag{1}$$

These intervals definitions, related to the QRS fiducial point, avoid the always problematic estimation of the J point to define the repolarization windows, although consider the heart rate effects [29].

The $\mathrm{rms}[t_i]$ time series was estimated for each recording by summing the rms difference series of each jth lead, $\mathrm{rms}^j[t_i]$ (t_i is the fiducial point of the ith beat). The $\mathrm{rms}^j[t_i]$ series were obtained as the rms difference values between the corresponding ECG segment (the ST segment or ST-T complex) of length L, $ecg_i^j[k]$ (k is the sample index), and the average or template interval, $\overline{ecg}^j[k]$ (evaluated from first 100 beats, representative of the initial ECG). The expression to calculate the $\mathrm{rms}[t_i]$ time series is, hence

$$\mathrm{rms}[t_i] = \sum_{j=1}^{leads} \mathrm{rms}^j[t_i] = \sum_{j=1}^{leads} \left[\frac{1}{L} \sum_{k=1}^{L} (ecg_i^j[k] - \overline{ecg}^j[k])^2 \right]^{1/2}. \tag{2}$$

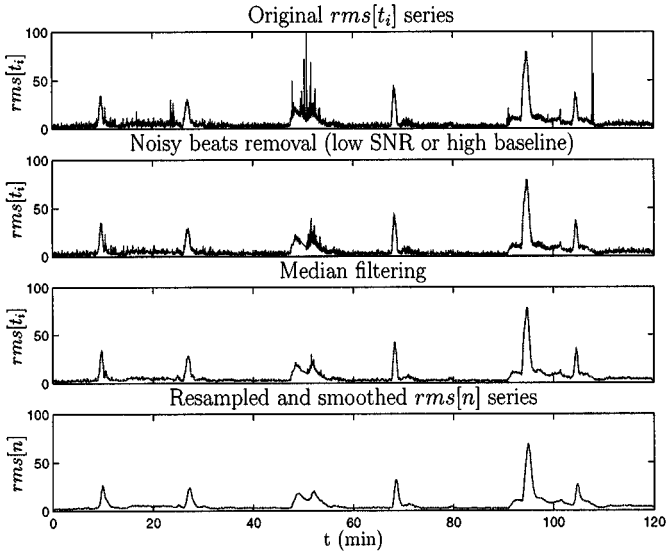


Fig. 2. Example of beats rejection (preprocessing stage) in the rms series of ST-T complex, and successive filtering stages (median filtering and exponential averaging). See text for details.

A median filter of length 5 samples was used for outlier rejection in the $\mathrm{rms}[t_i]$ series and then the time series was evenly resampled to 1 Hz (using linear interpolation to obtain $\mathrm{rms}[n]$ from $\mathrm{rms}[t_i]$). An exponential averager (time constant equal to 20 s) was further applied to smooth the series. The cleaning effects of the successive filtering stages over the rms series, as well as the effects of the beat rejection applied in the preprocessing, are shown in Fig. 2 (record $e0404$ from the *European ST-T database*). The importance of the noisy beats rejection stage can be noted

The final stage of the detector incorporates an adaptive amplitude threshold. The threshold accounts for slow drift changes in the repolarization period as caused by various nonischemic factors: effects of medication, heart-rate related changes or slow variations in the electrical axis of the heart. These slow changes are attenuated by applying an exponential averager that defines the baseline values for the $\mathrm{rms}[n]$ series, $\xi[n]$

$$\xi[n] = \xi[n-1] + \beta\,(\mathrm{rms}[n] - \xi[n-1]) \tag{3}$$

and that is estimated only from those beats considered as nonischemic by the detection algorithm. The β value adjusts the speed for slow changes to be considered as nonischemic events.

A threshold is finally used to determine the limits in the rms series where the variations, after subtraction of $\xi[n]$, are considered as repolarization (and potentially ischemic) events

$$\mathrm{rms}[n] - \xi[n-1] > \eta. \tag{4}$$

The detection algorithm operates at each instant n following the structure shown in Fig. 3. It tests the expression in (4) and

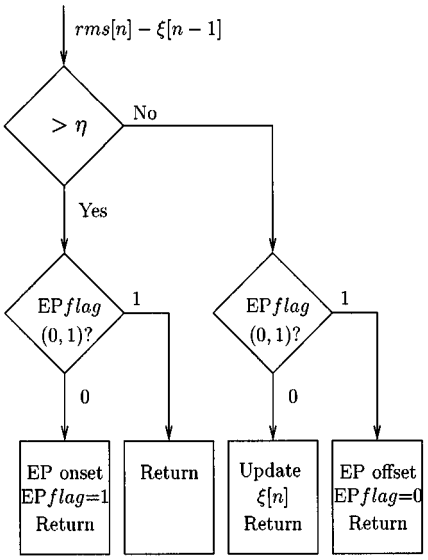


Fig. 3. Main structure of the detection algorithm that performs over the filtered $\mathrm{rms}[n]$ series.

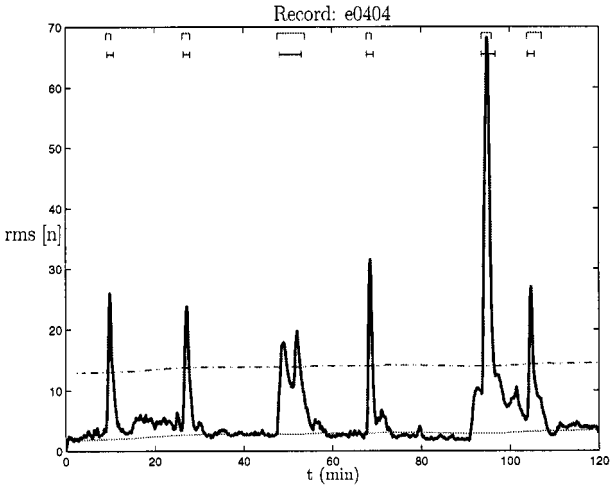


Fig. 4. Example of ST-T complex changes detection showing the annotated (⊓) and detected (⊢⊣) episodes intervals. The baseline estimation, $\xi[n]$, (dotted line) and plus the η threshold (dash-dotted line) are plotted over the $\mathrm{rms}[n]$ series.

then either determines the limits of an interval to be considered as an episode (EP), or updates the baseline $\xi[n]$. Two parameters are also included for setting up the minimum duration of episodes (45 s), and the minimum time distance between two successive episodes (2 min), but these are not shown in Fig. 3 for simplicity.

An example of the detector performance is shown in Fig. 4 as applied to detection of ST-T complex changes in the record $e0404$ from the *European ST-T database*. The annotated and detected intervals are shown in the upper part of Fig. 4; the baseline estimate, $\xi[n]$, and the threshold η are plotted over the $\mathrm{rms}[n]$ series. The first, second and fourth annotated episodes correspond to T wave changes without ST changes; the third manually annotated episode, to ST segment deviations; and the fifth and sixth, to variations annotated in both intervals.

TABLE II
EXTENDED ANNOTATION SETS OBTAINED AFTER INCLUSION OF SUBCLINICAL EVENTS WITH REPETITIVE PATTERN

	ST segment	**ST-T complex**
OR comb.	250	392
added eps. (recs)	30 (15)	37 (20)
total	280	429

C. Performance Measures

The detector performance needs to be evaluated by comparing the cardiologists' annotations and the detector output with regard to the following aspects [30]:

- detection rate;
- duration;
- magnitude of detected episodes.

First two aspects are evaluated in terms of sensitivity and positive predictivity for both detection rate (S, $+P$) and duration (S_D, $+P_D$), respectively [30].

The third aspect, related to the accuracy in the episodes magnitude estimation, is measured by comparing event-by-event the annotated amplitudes of the episodes (deviation peak as measured by the cardiologists) to the values obtained by the detector. The estimated linear correlation coefficient, r, between the two sets provides a measure of the detector linearity.

Two kinds of statistics are commonly used for detector validation: *gross statistics*, in which the episodes of all patients are assigned equal weights, and *averaged statistics*, in which every patient is assigned equal weights. We will direct our attention to averaged statistics to summarize the main results, since we did not find much difference with respect to gross statistics.

D. Correlation Analysis of Episodes with Repetitive Pattern

A repetitive pattern of changes was found in several recordings of the database. Although some of these patterns were not annotated by the cardiologists, thus leading to some false positive detections as shown in the results section, these may still have clinical importance; in some cases these subclinical events have a magnitude or duration slightly below the minimum requirements needed for annotation, and can precede other episodes in time. This finding of several borderline cases of ischemia has also been reported in other studies using the *European ST-T database* [5], [18], [21], [23]. Therefore, we have expanded the detector with a post-processor which detects these subclinical events by estimation of the episodes correlation in the $\mathrm{rms}[n]$ series domain.

We selected, after visual inspection of the $\mathrm{rms}[n]$ series, those recordings that showed ST segment or ST-T complex episodes repetitions not annotated by the cardiologists. A repetitive pattern of episodes was found in around 20% of the recordings (17% for ST segment and 22% for ST-T complex episodes). New extended sets of annotations (Table II) were obtained by addition of the new events that presented high likelihood in their energy evolution with respect to that of the largest episode annotated in each recording (the number of recordings where the new annotations came from are also included in parenthesis).

The post-processing stage analyzes the correlation coefficient between different episodes. In each recording, the largest de-

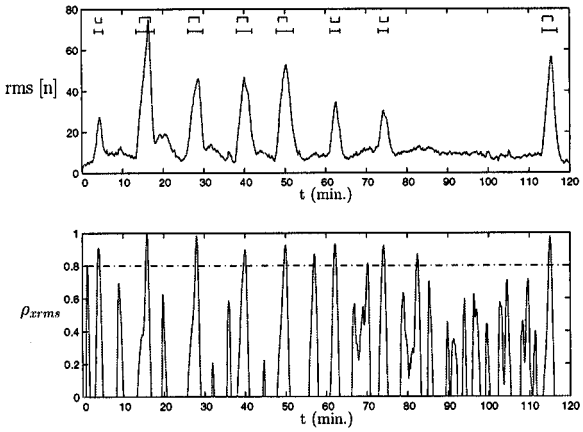


Fig. 5. Example of detection of repetitive ST segment subclinical events for the recording $e0103$ using the cross-correlation post-processor. Top: $\mathrm{rms}[n]$ series with originally annotated (⊓), manually added (⊔), and automatically detected (⊢⊣) episodes. Bottom: $\rho_{x\mathrm{rms}}$ correlation coefficient. Note that some peaks in $\rho_{x\mathrm{rms}}$ (e.g., around minute 57) are not detected because of the amplitude protection for $\mathrm{rms}[n]$ included in the correlation stage.

TABLE III
PERFORMANCE STATISTICS (IN PERCENTAGE) OF THE DETECTOR FOR ST SEGMENT AND ST-T COMPLEX CHANGES DETECTION

	Parameters		Averaged statistics			
Interval	η	β	S	$+P$	S_D	$+P_D$
ST	18.1	0.0083	84.7	86.1	75.3	68.2
ST-T	11.1	0.0017	85.0	76.3	77.8	60.3

tected episode was selected from the $\mathrm{rms}[n]$ time series and taken as the episode template for that patient. The normalized correlation coefficient, ρ, between the episode template, $\mathbf{x}[k]$, and the corresponding time series is defined by

$$\rho_{x\mathrm{rms}}[n] = \frac{\sum_{k=-N/2}^{N/2} x[k]\mathrm{rms}[k+n]}{\left[\sum_{k=-N/2}^{N/2} x^2[k] \sum_{k=-N/2}^{N/2} \mathrm{rms}^2[k+n]\right]^{1/2}} \quad (5)$$

where N is the template length. Those signal excerpts for which the correlation coefficient exceeded an experimentally selected threshold ($\rho > 0.8$), presenting an amplitude in the $\mathrm{rms}[n]$ series (once the baseline $\xi[n]$ has been subtracted) at least exceeding 25% of the template episode amplitude (to remove highly correlated episodes with negligible peaks), were detected as subclinical events. The validation of the detector combined with the post-processor was done for the extended sets of episodes, see Table II.

An example of the performance is shown in Fig. 5 for ST segment changes in the recording $e0103$. In the upper panel, the $\mathrm{rms}[n]$ series with the original annotations, manually added (centered around minutes 4, 62, and 74) and automatically detected episodes are shown. The estimated $\rho_{x\mathrm{rms}}$ correlation coefficient, which constitutes the basis for the detection of subclinical events, is shown in the bottom panel.

III. RESUTLS

The detector was applied to the *European ST-T database*. The results of the validation on all the recordings, using the OR sets described in Table I, are shown in Table III. These results present performance statistics ($S/+P$) for the ST segment episodes of 84.7/86.1% in episodes detection, and 75.3/68.2% for ischemia duration estimation. For changes in the entire ST-T complex, the results of sensitivity (both in episodes detection and duration measure) reached similar levels, but presented a significant decrease in the positive predictivity.

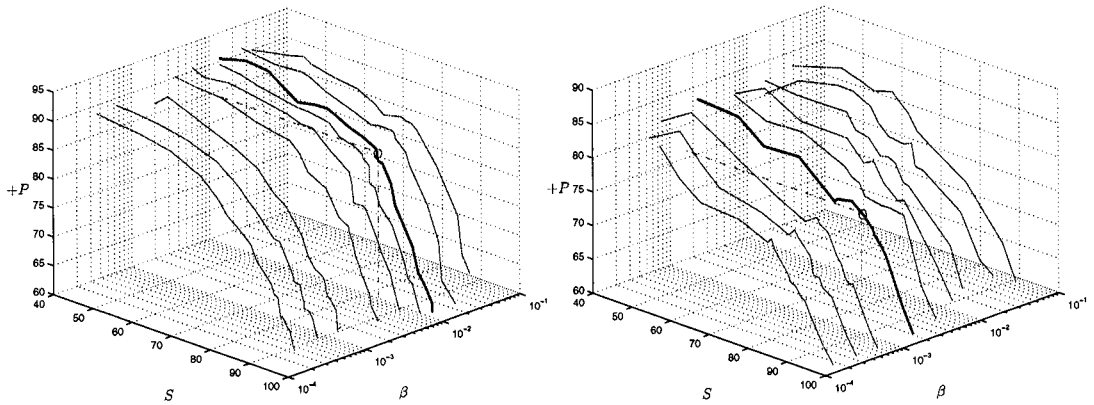
The *receiver operating characteristics* (ROC) curves (S versus $+P$) corresponding to ST segment and ST-T complex episodes detection and obtained for different values of η and β are shown in Fig. 6(a) and (b), respectively. The ROC's correspond to episode detection and similar curves define the performance in episode duration. The optimal point was selected for each segment maximizing the geometrical mean of the statistics performance parameters (S, $+P$, S_D, and $+P_D$) obtained for each ROC point (defined by a couple of η, β values). The ROC's corresponding to different but close β values yield similar performances, although the optimal points in each curve may correspond to different η values. However, for β values far from the optimal point the performance of the detector deteriorates.

The detector accuracy was estimated by calculating the linear correlation coefficient, r, between the deviations as measured by the cardiologists and the output of the detector at the maximum deviation of the episode. In Fig. 7 the event-by-event comparison is shown between both sets of measurements for ST segment deviations (the values of the lead-related $\mathrm{rms}^j[n]$ series at each annotated episode peak, and signed according to the deviation, are represented in the horizontal axis; the manually annotated deviations are shown in the vertical axis). The correlation coefficient was $r = 0.963$, and the regression line was defined by $ST = 4.33 \cdot \mathrm{rms}^j - 10.72$. The detector linearity for ST-T complex changes was also evaluated (comparing the ST-T complex rms^j series values at each annotated episode peak of ST segment or T wave with respect to the database annotations) obtaining a lower correlation coefficient, $r = 0.912$, and a regression line defined by $STT = 12.95 \cdot \mathrm{rms}^j + 2.79$.

Once the basic detector structure was validated, the extended set obtained by adding new annotations (Table II), was considered. First, the basic detector structure was studied on this set (composed of 280 and 429 events for ST segment and ST-T complex, respectively), and then the post-processor was included ($+\rho$-stage) for detection of subclinical events. All these results are presented in Table IV. These results indicate that the post-processor finds the subclinical events otherwise missed, providing an improvement of the detector performance for detecting ST segment subclinical events ($S/+P$ from 85/86 to 90/85) similar to that obtained for ST-T complex subclinical events ($S/+P$ from 85/76 to 89/76).

IV. DISCUSSION

Comparative performance statistics are presented in Table V for different detectors using the *European ST-T database*: second and third columns (left part of the table) show S and $+P$ values for each detector in their optimal operating points;



(a) ROCs for ST segment episodes detection. Optimal point selected at (β = 0.0083, η = 18.1).

(b) ROCs for ST-T complex episodes detection. Optimal point selected at (β = 0.0017, η = 11.1).

Fig. 6. ROC curves for detection of (a) ST segment, and (b) ST-T complex episodes. The ROC's curves (S versus $+P$ representations) have been calculated varying η for several values of β.

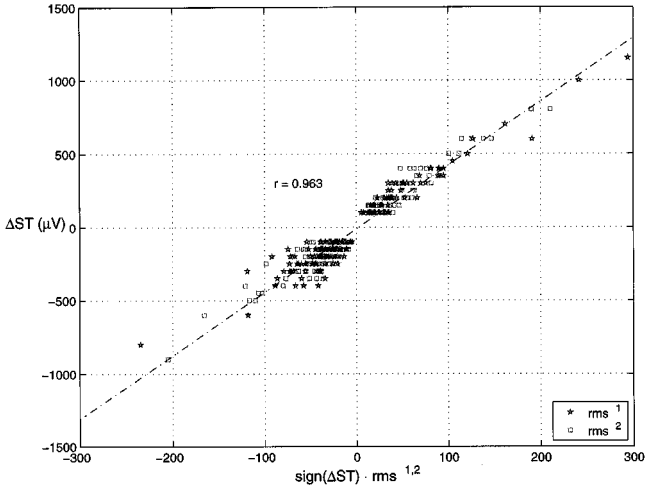


Fig. 7. Accuracy for estimating the ST segment deviation magnitude of the annotated events: regression line and correlation coefficient. See text for details.

TABLE IV
DETECTOR PERFORMANCE STATISTICS (AVERAGED AND EXPRESSED AS PERCENTAGE) WITH AND WITHOUT USE OF THE CORRELATION STAGE ON THE EXTENDED SET.

Method	Int.	S	$+P$	S_D	$+P_D$
RMS	ST	81.7	88.9	73.5	69.8
+ ρ-stage	ST	89.7	84.9	84.7	64.5
RMS	ST-T	83.0	79.7	76.5	62.2
+ ρ-stage	ST-T	89.2	76.2	85.6	59.3

the fourth and fifth columns (right part of the table) show $+P$ values obtained with the rms detectors (rms and rms $+\rho$), respectively, after forcing them to obtain the same S value as the other detectors (thus, an identical S is found in each row and the comparison is done attending $+P$). Note that the new operating points for the rms detectors do not correspond to their optimal values but facilitates the comparison. The detectors presented in [18] and [20] were validated using the same 250 ST segment episodes set used here (see Table I), and

TABLE V
PERFORMANCE STATISTICS COMPARISON WITH OTHER DETECTORS IN OPTIMAL OPERATING POINTS (COLUMNS 2 AND 3), AND AFTER FORCING THE rms DETECTORS TO OBTAIN THE SAME S THAN THE OTHER SYSTEMS (COLUMNS 4 AND 5). SEE TEXT FOR DETAILS.

Method	S	$+P$	$+P$ RMS	$+P$ RMS+ρ
RMS	85	86		
*RMS + ρ-stage	90	85		
Taddei et al. [18]	84	81	87	87
**Maglaveras et al. [31]	89	78	80	85
Jager et al. [20]	87	88	83	86

*Tested on the extended annotation set (280 events).

**Only tested for ST segment episodes annotated on the first lead (160 events).

the detector of [31] was only tested for ST segment episodes annotated on the first lead (160 events). On the other hand, the rms $+\rho$-stage detector was tested on the extended annotation set (280 events). Although our detector is based on simple processing stages, its performance is of the same order, or better, than those obtained for algorithms based on much more sophisticated techniques. The present detector has the great advantage of detecting both ST segment deviations and ST-T complex changes: no previous detectors of ST-T complex changes have been validated. Many of the detectors referred to in the Introduction have not been validated using an annotated database, thus making it impossible to establish a performance comparison.

Most of the previous work in this area did not evaluate the accuracy for estimating the deviation magnitude of the ischemic events. This information could be important for the clinician: once an event has been detected, its magnitude should be defined to estimate clinical implications. With respect to this point, our detector presented a highly linear behavior and a close coincidence with the manual annotations. We may conclude the comparison of the different detectors by asserting that it seems difficult to increase the present detection performances; further improvement might be related to an over-training on the *European ST-T database*. Regarding this, it is important to develop new databases of this type, e.g., [32], to test algorithms for ischemia detection.

The decrease in positive predictivity when detecting ST-T complex changes instead of ST segment deviations, may be due to several factors. One of them is the intrinsic difficulty to manually detect T wave changes (obviously more complicated to detect than ST deviations, due to the need of a T wave template for comparison) that would yield to the absence of annotations for several episodes that get detected by the automatic detector. Another factor may be the wider variety of changes (not always related to ischemia) that can be present in the whole repolarization period and, therefore, makes it difficult to avoid false detections.

The analysis intervals had fixed lengths although starting at a heart rate (HR)-dependent distance from the QRS fiducial point. The interval lengths were selected in order to include the appropriate signal segment (300 ms was considered long enough to include most of the T wave energy even for a slow HR and short enough to avoid inclusion of energy from the next beat in case of a fast HR). For uses of the detector in situations where the HR is expected to reach extreme values (e.g., $>$ 150 bpm during stress test), the use of window lengths adjusted to the RR interval is suggested [29]. However, for ambulatory monitoring purposes the present structure did not affect the performance. In fact, the validation results did not change significantly even when the interval onset was selected at a fixed point instead of at a HR-dependent point.

The cross-correlation study showed that a significant number of patients presented a repetitive ischemic pattern (around 20%). Such potentially ischemic episodes that exhibited the same variations pattern could be due to coronary vasospasms (Prinzmetal's angina) [33]. When the basic detector structure was applied to the extended set of annotations, then the S value was obviously reduced (from 85% to 82% for ST segment changes, and from 85% to 83% for ST-T complex changes) as a consequence of that many new episodes (subclinical events) were not detected, but the $+P$ value increased (from 86% to 89%, and from 76% to 80%) since some events that in the original set were false detections, further accounted for as correct detections. When the correlation stage was added the S value increased significantly (up to 90% and 89%, for ST segment and ST-T complex, respectively), corresponding to a better detection of the new episodes, and the $+P$ value decreased slightly (to 85% and 76%, for ST segment and ST-T complex, respectively) due to that the extra stage has associated its own false positive detections. The correlation stage improved the detector performance on the extended annotation set, which contains small episodes or subclinical events below the usual requirements for ischemia detection.

Changes in body position are sometimes mistaken for as myocardial ischemia during ambulatory ECG monitoring. In this work the problem of nonischemic events has not been addressed, although the whole database (including the two recordings that have axis shifts annotated instead of ischemic episodes) has been used for the testing. The cancelation of these events and maybe other potential axis shifts not annotated, which yielded false detections would imply an improvement in the positive predicitvity of the detector (the rejection of these two files in the evaluation yields an improvement of 2% in $+P$). It would be desirable to expand the present detector structure to handle changes in body position.

Finally, it should be pointed out that different lead configurations are included in the *European ST-T database*, thus presenting a large variety of two lead combinations. This property constitutes an additional difficulty in the selection of the detector parameters since ischemia is reflected differently in different leads. Detection based on identical lead configuration is likely to yield better performance.

V. Conclusion

The present detector is based on simple processing stages. Its performance is comparable to or even better than those of more complex algorithms. The detector handles not only ST segment deviations but also entire ST-T complex changes, thereby providing a more complete approach to the detection of ischemic episodes. Validation on the *European ST-T database* showed results of sensitivity/positive predictivity of 85/86%, and 85/76%, respectively, for ST segment deviations and ST-T complex changes. A post-processor based on a cross-correlation analysis in the rms series domain detected subclinical events with repetitive patterns (found in around 20% of the recordings), and improved the performance to 90/85%, and 89/76%, for ST segment deviations and ST-T complex changes, respectively.

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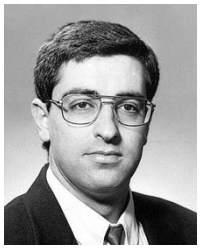

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