Tuning a Real-Time Detector of Transient Cardiac Ischemic Episodes on the Long-Term ST Database according to the Annotation Protocol B

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Abstract

This study revisits a real-time ischemia detector developed over the Long-Term ST (LTST) database according to the transient ST episode annotations for protocol A. We have studied how to adapt the initial detector in order to comply with the ischemia annotation protocol B requirements on the same database, a protocol similar to what is being used in clinical practice. Secondly we have studied to improve the initial algorithm.

The intermediate results in terms of sensitivity/positive predictivity after a first detection step were 83.15%/56.75% and improved to 81.17%/74.83% after a discrimination step based on the bagging of decision tree method. These results improve our previous ones and are comparable to other results reported for this database, with the advantage that this algorithm could analyze the ECG signal in real-time.

1. Introduction

The electrocardiogram (ECG) monitoring is a common practice to obtain information about the severity and duration of cardiac ischemic episodes. Changes (elevations or depressions) of the ST-segment in the ECG signal may indicate ischemia. Diurnal or postural changes and changes in ventricular conduction may induce apparently similar changes in the ST-segment, and thus hinder the automatic detection of ischemia and increase the false alarm rate. This shows up most acutely in ambulatory ECG, where the patient can move freely and is not confined to a bed. For this kind of patients, ischemia real-time detection may have applicability in the growing field of telemedicine [1]. Moreover, real-time algorithms might be more suitable in environments with computational restrictions.

There are several algorithms proposed in the literature for the automated detection of ischemia, most of them developed over the European Society of Cardiology ST-T database (ESC DB). Although some of these methods might be adapted to be executed in real-time, only a few of them explicitly address the real-time analysis case where less information (only past and present) is available to take a decision.

The long-term ST database (LTST DB) [2] was released in 2003, but still there are few ischemia detection algorithms [3–5] using this database. Performance drops were reported for some algorithms developed over the ESC DB and validated later over the LTST DB [4].

The LTST DB contains 86 annotated ECG Holter records from 80 patients, collected during routine clinical practice. The annotation criteria of this database is lead oriented: a ST segment episode (ischemic or heart-rate-related) was annotated in a recorded lead if it reaches a magnitude of V_{min} μV or more, throughout a continuous interval of at least T_{min} seconds. The annotators followed three different annotation protocols by using the next thresholds:

- Protocol A: V_{min} = 75μV and T_{min} = 30s
- Protocol B: V_{min} = 100μV and T_{min} = 30s
- Protocol C: V_{min} = 100μV and T_{min} = 60s

In [3] we proposed an algorithm for real-time detection of cardiac ischemic episodes developed over the LTST database, considering the ST-segment episode annotations provided for the protocol A. In this work we use the LTST database and its annotation protocol B in order to tune and improve our initial algorithm. The limits of the protocol B are more similar to the ones used in clinical practice and the results for annotation protocol B are more used in the literature when comparing performance. Therefore, one of the goals of this study is to make easier a fair comparison with related works.

The following section contains a description of the algorithm with the new settings and improvements. Their results are presented in the third section. The last section contains the conclusions.

2. Methods

The detection algorithm of transient cardiac ischemic episodes, discussed here, is a real-time approach based on the continuous analysis of the ECG samples picked up regularly, from each monitored lead, and combines signal processing methods (time domain analysis) to detect possible ischemic episodes (the *detection step*) with artificial intelligence techniques (bagging of decision trees) to discriminate between ischemic and non-ischemic episodes (the *discrimination step*). As the rest of the cardiac ischemia detectors that have been published, the algorithm makes no difference between ischemic and heart-rate related episodes. The heart-rate related episodes, very similar to ischemia, were labeled in the LTST database as such based on clinical information from the subject.

2.1. Detection step

First, the detection step includes an ECG delineation in order to be able next to extract features from each beat that makes up the ECG signal (see [3] for more details). One of the most important feature to be extracted is the ST_{level}.

2.1.1. ST_{level} measurement

Transient ST-segment episodes are detectable in ECG signals via slow ST-segment deviations. The difference between normal beats and beats with ST-segment depression, recorded from the same patient half an hour apart, can be appreciated in Figure 1.

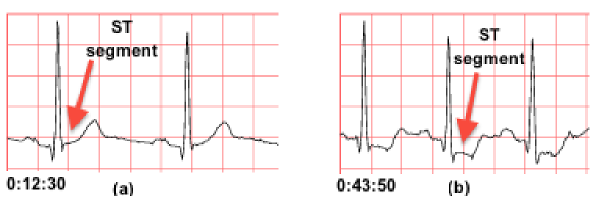

Figure 1. ECG from patient s20031 in LTST database. Recording time in the bottom (hh:mm:ss). a) normal beats b) ST-segment deviated beats (depression).

In order to compute those deviations, the authors of the LTST database measured the ST_{level} using a protocol[1] that depends on the J point location [2]. The detection algorithm presented in [3] follows that method.

The way the ST_{level} is measured may affect the detection performance of ST-segment episodes. In order to improve the performance of our initial algorithm, in this work we have tested another ST_{level} measurement method introduced in [6] and already used in the literature [4, 7] with similar purpose.

According to that method, the ST_{level} has been estimated at each *i*th beat and lead of the ECG signal using a heart-rate related sample reference (n^i_{ST}):

[1]The ST_{level} measurement point is considered at 80ms after J point if HR $<$ 100 (heart rate is less than 100 beats per minute), at 72ms after J point if 100 $\leq$ HR $<$ 110, at 64ms after J point if 110 $\leq$ HR $<$ 120 and at 60 ms after J point if HR $\geq$ 120

$$n^i_{ST} = \theta_i + \frac{40}{1000} f_s + 1.3\sqrt{\frac{rr_i}{1000} f_s} \qquad (1)$$

where θ_i represents the sample of the QRS fiducial point defined as the center of gravity of the QRS complex, f_s is the sampling frequency and $rr_i = \theta_i - \theta_{i-1}$.

2.1.2. Noise rejection

The portable nature of some ECG registering devices (Holters for the LTST database) demands strong noise rejection policies in order to avoid false alarms due to increased levels of motion artifacts and environmental noise.

We have applied some noisy beat exclusion rules with the goal of deleting the periods of noisy beats that may distort the ST level measurement and that do not have to be considered in the ischemia analysis process. Apart from exclusion rules that prevent from analysing the signal that corresponds to "impossible" beats, a rule has been introduced in order to reject those beats that show noticeably different ST-segment values from both the values recorded for their neighbours and a computed mean. The root mean square (RMS) of the ST-segment computed from n^i_{ST} to $n^i_{ST} + 50$ ms for each *i*th beat (ST^{50}_{RMS}) has been used for the comparison. There have been rejected from the analysis: isolated beats and the first of each two consecutive beats that differed more than 10 dB from both the previous recorded beat and the running filtered ST^{50}_{RMS} series. The filter used was a low-pass Butterworth filter [3].

2.1.3. ST_{level} series computing

The ST_{level} series have been obtained by: 1) extracting ST_{level} from each beat noise free, 2) resampling it with a frequency of two samples per second and 3) smoothing the result with a Butterworth filter [3]. This was the input to a set of threshold rules, for detecting ST-segment episodes.

2.1.4. ST-segment episodes detection

The detector uses four sliding windows of 120, 60, 30 and 15 seconds respectively over ST_{level} series. Several deviations are computed with respect to the running ST_{level} series: 1) $\triangle\mathrm{ST}^{120}_{level}$, $\triangle\mathrm{ST}^{60}_{level}$, $\triangle\mathrm{ST}^{30}_{level}$ and $\triangle\mathrm{ST}^{15}_{level}$ (the maximum deviation registered over ST_{level} series in the corresponding sliding window) and 2) $\triangle\mathrm{ST}^{ref}_{level}$ (the deviation with respect to an exponential running average with a forgetting factor set to 10^{-4}) [3]. Threshold-based rules for these deviations determine the onset of a ST-segment episode.

These thresholds have been adjusted to comply with the ischemia annotations for protocol B. Thus, the detector has been configured to detect the onset of a ST-segment episode when the $\triangle ST^{ref}_{level}$ and $\triangle ST^{120}_{level}$ reach a magnitude of 50μV and 20μV respectively. Additional checks have been done for 1) $\triangle ST^{30}_{level}$ against $\triangle ST^{60}_{level}$ deviation and 2) $\triangle ST^{60}_{level}$ against $\triangle ST^{120}_{level}$ deviation in order to ensure the continuity and maintenance of the ST deviation trend over the last two minutes.

The episodes detected according to these rules are the input to the next discrimination step.

2.2. Discrimination step

This step is intended to discriminate between ST-segment episodes related to ischemia or heart-rate from those caused by body position changes, conduction changes or lapse in the estimation made in the previous detection step. A classifier was made for this task.

2.2.1. Feature extraction

The analysis over the four sliding windows and the computing of the reference level (seen in the detection step) were extended to other time series that were obtained by extracting several features (F), beat by beat and filtering them in the same way as the ST_{level} series.

Table 1. List of features extracted from each beat

Feature	Description
ST_{level}	The ECG signal amplitude at the ST measurement point
J_{level}	The ECG signal amplitude measured at the J-point (offset of the QRS complex)
$ST_{\angle}$	The ST-segment slope
HR	The heart rate
QR_d	Time elapsed from the onset of the QRS complex until its peak
RS_d	Time elapsed from the peak until the offset of the QRS complex
QRS_d	The QRS complex duration (from the onset to the offset)
QR_{RMS}	The RMS of the signal between the onset and the peak of the QRS complex
RS_{RMS}	The RMS of the signal between the peak and the offset of the QRS complex
ST_{RMS}	The RMS of the signal from J to J + 120ms
$ST_{RMS_{50}}$	The RMS of 50ms signal, starting from the ST measurement point, as proposed in [7]
QRS_U	The upslope of the R wave
QRS_D	The downslope of the R wave
SNR	The signal to noise ratio

Table 1 shows the list of all the beat features (F). The QRS_U and QRS_D features where calculated using a modified technique proposed in [8]. The SNR feature was estimated as proposed in [7].

For each ST-segment detected episode and for each of the filtered F series, the corresponding deviations $\triangle F^*$ have been calculated, where $* \subset \{ref, 120, 60, 30, 15\}$.

2.2.2. Feature selection

Not all of $\triangle F^*$ deviations are relevant for the classification task and some of them may be redundant. The correlation-based feature subset selection method [9] has been used to select the most relevant ones. This method considers both the individual predictive ability of each feature and the degree of redundancy between them.

28 features were selected to be used for the classification of ischemic episodes according to the protocol B requirements. The selected features were deviations registered in ST_{level}, J_{level}, $ST_{\angle}$, ST_{RMS}, $ST_{RMS_{50}}$, QRS_U, RS_{RMS}, SNR, HR, QR_{RMS}, QR_d and QRS_d series.

Deviations extracted from ST_{RMS} series proved to be more relevant for the classification task than the ones calculated for $ST_{RMS_{50}}$ series. Deviations extracted from QRS_U and SNR series have been considered relevant. No feature extracted from QRS_D series has been picked up by the selection tool.

2.2.3. Classification of ST-segment episodes

Bagging of decision trees has been used for the classification task as described in [3]. The model has been made up by 21 decision trees and it has been configured to classify a ST-segment episode as non-ischemic based on the agreement of 15 of the 21 base classifiers. It presents a specificity of 42.44%, i.e. it rejects almost half of the non-ischemic episodes detected in the detection step.

3. Results

The results obtained for protocol B in the detection step are shown in Table 2. The criterion specified in [10] has been used as matching criterion in order to compute the sensitivity (S) and predictivity (P), according to both gross (g) and average (a) statistics and in terms of both number of episodes (STE) and duration of episodes (STD).

Table 2. Intermediate results over LTST DB after the detection step.

	S(g)	S(a)	P(g)	P(a)
STE%	83.15%	81.19%	56.75%	58.05%
STD%	69.87%	69.42%	45.79%	54.46%

The intermediate results show higher positive predictivity (an increase of about 10 points) in the detection step than the algorithm in [3]. However, the new ST level computing method implies a slight decrease in sensitivity, as some heart-rate related episodes are no longer detected. Sensitivity decrease has not been observed for clearly ischemic episodes.

A significant improvement of the positive predictivity (from 56.75% to 74.83%) has been obtained by applying the discrimination step. Final real-time detection algorithm results over LTST database are shown in Table 3.

Table 3. Results over LTST DB after the discrimination step.

	S(g)	S(a)	P(g)	P(a)
STE%	81.17%	77.98%	74.83%	70.05%
STD%	68.42%	66.67%	57.97%	62.21%

The sensitivity of the algorithm (81.17%) is slightly higher than the one reported in [5] (79.63%). The positive predictivity (74.83%) is still lower than the one obtained in [5] (78.12%). The algorithm outperforms both in sensitivity and predictivity the results obtained in [4]. Nevertheless, we have to take into account that this comparison is made with off-line methods, not suitable for real-time analysis.

4. Conclusions

In this paper a real-time detection of transient cardiac ischemic episodes was tuned and improved, in order to comply with the ischemia annotation protocol B requirements over LTST database.

The detection algorithm consists of a detection step of ST-segment episodes and a discrimination step of ischemic from non-ischemic episodes. In the detection step: 1) a new measurement method proposed in the literature for the ST level has been adopted; 2) detection thresholds have been adjusted to comply with the ischemia annotations for protocol B, and additional checks have been done on the continuity and maintenance of the ST deviation trend over time.

In the discrimination step, we evaluated several features, recently proposed in the literature, for ischemia discrimination from non-ischemic events. The individual predictive ability of each feature and the degree of redundancy between them have been considered. Several new features have been found suitable and used for the real-time ischemia discrimination from non ischemic ST-segment changes. A bagged decision tree model has been trained according to the annotations for protocol B. The model uses a voting scheme that allows the posterior adjustment of the final decision according to their confidence level.

The detection results improve our previous ones and are comparable to other results reported for this database, with the advantage that this algorithm could analyse the ECG signal in real-time.

References

[1] Goñi A, Burgos A, Dranca L, Rodríguez J, Illarramendi A, Bermúdez J. Architecture, cost-model and customization of real-time monitoring systems based on mobile biological sensor data-streams. Computer Methods and Programs in Biomedicine 2009;In Press, Corrected Proof:–. ISSN 0169-2607.

[2] Jager F, Taddei A, Moody GB, Emdin M, Antolic, Dorn R, Smrdel A, Marchesi C, Mark R. Long-term ST database: a reference for the development and evaluation of automated ischaemia detectors and for study of the dynamics of myocardial ischaemia. Med Biol Eng Comput 2003;41:172–182.

[3] Dranca L, Goñi A, Illarramendi A. Real-time detection of transient cardiac ischemic episodes from ecg signals. Physiological measurement 2009;30(9):983.

[4] Minchole A, Skarp B, Jager F, Laguna P. Evaluation of a root mean squared based ischemia detector on the long-term st database with body position change cancellation. In Computers in Cardiology. Sept. 2005; 853–856.

[5] Smrdel A, Jager F. Automated detection of transient ST-segment episodes in 24h electrocardiograms. Med Biol Eng Comput 2004;42:303–311.

[6] Badilini F, Zareba W, Titlebaum EL, Moss AJ. Analysis of st segment variability in holter recordings. Noninvasive Electrocardiology Clinical Aspects of Holter Monitoring Frontiers in Cardiology London UK WB Saunders Company Ltd 1996;357–372.

[7] Minchole A, Jager F, Laguna P. Discrimination between ischemic and artifactual {ST} segment events in holter recordings. Biomedical Signal Processing and Control 2010;5(1):21 – 31. ISSN 1746-8094.

[8] Pueyo E, Sornmo L, Laguna P. Qrs slopes for detection and characterization of myocardial ischemia. Biomedical Engineering IEEE Transactions on 2008;55(2):468–477.

[9] Hall MA. Correlation-based Feature Subset Selection for Machine Learning. Ph.D. thesis, University of Waikato, Hamilton, New Zealand, 1998.

[10] Jager F, Smrdel A, Mark RG. An open-source tool to evaluate performance of transient ST segment episode detection algorithms. In Computers in Cardiology 2004. IEEE Press, 2004; 585–588.

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