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

Lacramioara Dranca¹, Alfredo Goñi², Arantza Illarramendi²

¹ Centro Universitario de la Defensa, Zaragoza, Spain
² University of the Basque Country, Donostia - San Sebastián, Spain

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: \(V_{min} = 75\) µV and \(T_{min} = 30s\)
- Protocol B: \(V_{min} = 100\) µV and \(T_{min} = 30s\)
- Protocol C: \(V_{min} = 100\) µV 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\textsubscript{level}.

2.1.1. ST\textsubscript{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.](image)

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

The way the ST\textsubscript{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\textsubscript{level} measurement method introduced in [6] and already used in the literature [4, 7] with similar purpose.

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

\[
n_{ST}^i = \theta_i + \frac{40}{1000} f_s + 1.3 \sqrt{\frac{rr_i}{1000}} f_s \tag{1}
\]

where \(\theta_i\) 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 \(n_{ST}^i\) to \(n_{ST}^i + 50\) ms for each \(i\)th beat (\(ST_{RMS}^{50}\)) 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\textsubscript{level}\textsubscript{RMS} series. The filter used was a low-pass Butterworth filter [3].

2.1.3. ST\textsubscript{level} series computing

The ST\textsubscript{level} series have been obtained by: 1) extracting ST\textsubscript{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\textsubscript{level} series. Several deviations are computed with respect to the running ST\textsubscript{level} series: 1) \(\Delta ST_{level}^{120}\), \(\Delta ST_{level}^{60}\), \(\Delta ST_{level}^{30}\) and \(\Delta ST_{level}^{15}\) (the maximum deviation registered over ST\textsubscript{level} series in the corresponding sliding window) and 2) \(\Delta ST_{level}\) (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.
episode when the $\Delta ST_{level}^f$ and $\Delta ST_{level}^{120}$ reach a magnitude of 50$\mu$V and 20$\mu$V respectively. Additional checks have been done for 1) $\Delta ST_{level}^{30}$ against $\Delta ST_{level}^{120}$ deviation and 2) $\Delta ST_{level}^{60}$ against $\Delta ST_{level}^{120}$ 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

<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ST$_{level}$</td>
<td>The ECG signal amplitude at the ST measurement point</td>
</tr>
<tr>
<td>J$_{level}$</td>
<td>The ECG signal amplitude measured at the J-point (offset of the QRS complex)</td>
</tr>
<tr>
<td>ST</td>
<td>The ST-segment slope</td>
</tr>
<tr>
<td>HR</td>
<td>The heart rate</td>
</tr>
<tr>
<td>QR$_d$</td>
<td>Time elapsed from the onset of the QRS complex until its peak</td>
</tr>
<tr>
<td>RS$_d$</td>
<td>Time elapsed from the peak until the offset of the QRS complex</td>
</tr>
<tr>
<td>QRS$_d$</td>
<td>The QRS complex duration (from the onset to the offset)</td>
</tr>
<tr>
<td>QR$_{RMS}$</td>
<td>The RMS of the signal between the onset and the peak of the QRS complex</td>
</tr>
<tr>
<td>RS$_{RMS}$</td>
<td>The RMS of the signal between the peak and the offset of the QRS complex</td>
</tr>
<tr>
<td>ST$_{RMS}$</td>
<td>The RMS of the signal from J to J + 120ms</td>
</tr>
<tr>
<td>ST$_{RMS}^{30}$</td>
<td>The RMS of 50ms signal, starting from the ST measurement point, as proposed in [7]</td>
</tr>
<tr>
<td>QRS$_U$</td>
<td>The up-slope of the R wave</td>
</tr>
<tr>
<td>QRS$_D$</td>
<td>The down-slope of the R wave</td>
</tr>
<tr>
<td>SNR</td>
<td>The signal to noise ratio</td>
</tr>
</tbody>
</table>

Table 1 shows the list of all the beat features ($F$). The QRS$_U$ and QRS$_D$ features were 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 $\Delta F^*$ have been calculated, where $* \subset \{ref, 120, 60, 30, 15\}$.

#### 2.2.2. Feature selection

Not all of $\Delta F^*$ 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, J, ST$_{RMS}$, ST$_{RMS}^{30}$, 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$_{RMS}^{30}$ 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

<table>
<thead>
<tr>
<th></th>
<th>S(g)</th>
<th>S(a)</th>
<th>P(g)</th>
<th>P(a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>STE%</td>
<td>83.15%</td>
<td>81.19%</td>
<td>56.75%</td>
<td>58.05%</td>
</tr>
<tr>
<td>STD%</td>
<td>69.87%</td>
<td>69.42%</td>
<td>45.79%</td>
<td>54.46%</td>
</tr>
</tbody>
</table>

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.

<table>
<thead>
<tr>
<th></th>
<th>S(g)</th>
<th>S(a)</th>
<th>P(g)</th>
<th>P(a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>STE%</td>
<td>81.17%</td>
<td>77.98%</td>
<td>74.83%</td>
<td>70.05%</td>
</tr>
<tr>
<td>STD%</td>
<td>68.42%</td>
<td>66.67%</td>
<td>57.97%</td>
<td>62.21%</td>
</tr>
</tbody>
</table>

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 predictability 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


Address for correspondence:
Lacramioara Dranca
Centro Universitario de la Defensa, Ctra. de Huesca s/n, Zaragoza, Spain
http://cud.unizar.es/dranca