An Algorithm to Distinguish Ischaemic and Non-ischaemic ST Changes in the Holter ECG

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Abstract

Changes in the ECG ST segment are often observed in patients with myocardial ischaemia. However, non-ischaemic changes in ST level are also common thereby limiting ischaemia detection accuracy. The aim of this study was to devise an algorithm and determine its accuracy in distinguishing between ischaemic and non-ischaemic changes in the ECG ST-segment, using expertly annotated ECG data sets as a gold standard reference. The algorithm considered only the change in ST relative to a baseline ST level (ΔST) provided by the PhysioNet database, and based on simple level thresholding within specified time windows. An initial score of 82.3% (accuracy 91.1%, with sensitivity 99.0% and specificity 88.8%) was achieved for the learning set. By making slight modifications to the algorithm and introducing principal components of ST it was not possible to improve the original algorithm. The original algorithm was therefore left as our challenge entry achieving an accuracy of 90.7% for the test data set (score of 81.4%, entry 1, 1 May 2003).

1. Introduction

Therapeutic intervention to reduce transient myocardial ischaemic episodes could significantly improve the quality of life in affected subjects by reducing morbidity and mortality. The current methods of diagnosing these ischaemic events include cardiovascular imaging of the coronary arteries [1]. However, such specialised and resource intensive techniques are, arguably, unsuitable for studying ischaemic events brought on by activities of daily living in any one individual. Another technique, based on the analysis of the ECG waveform, has shown promise since abnormalities in the repolarization of ischaemic myocardial regions are visible in the ST segment of the ECG [2,3]. Although changes in ST elevation/depression can be quantified they can also occur because of a wide variety of other causes, including changes in heart rate, conduction pattern, hyperventilation, electrolyte abnormalities, response to medication, response to temperature changes, position of the subject, and noise in the ECG [4,5]. Despite these uncertainties, ECG measurements can be highly sensitive, easy to do, and lend themselves to ambulatory (e.g. 24 hour) assessments [6-8] and computer-based automated analyses [9-11]. If it were possible to accurately distinguish between ischaemic and non-ischaemic ST changes in ambulatory ECG recordings made during subjects' normal activities, the benefits could be immediate and substantial to the patient.

The aims of this study were therefore a) to produce a novel algorithm to distinguish ischaemic and non-ischaemic ST changes in the ECG waveform and b) to determine the accuracy of the algorithm using expertly annotated ambulatory ECG data sets as a reference.

2. Methods

2.1. Basic algorithm

Data for the changes in ST (ΔST) provided by PhysioNet were used. An example of ΔST is shown in figure 1. Event start times (T_s), for which the expertly classified ST changes (ischaemic or non-ischaemic) were known, were also provided and used in the development of the algorithm. ΔST represents the difference in ST between the current ST level and the baseline level. Principal components of ST provided by PhysioNet were also used in the optimization of the algorithm.
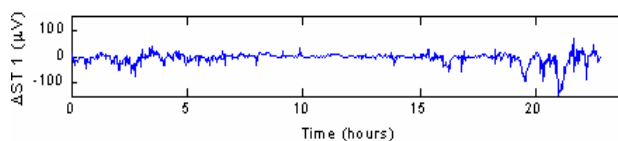

Figure 1. Example 24 hour ΔST recording from learning data set, as provided by PhysioNet.

The algorithm was based on the premise that ischaemic ST changes are large relative to non-ischaemic changes and that they are maintained for a period of time. The algorithm classified events as ischaemic if at the start of the event ΔST was greater than a threshold ΔST (V_{thres}), and before the end of the event ΔST maintained a minimum level (V_{min}) for a period of time (T_{min}).
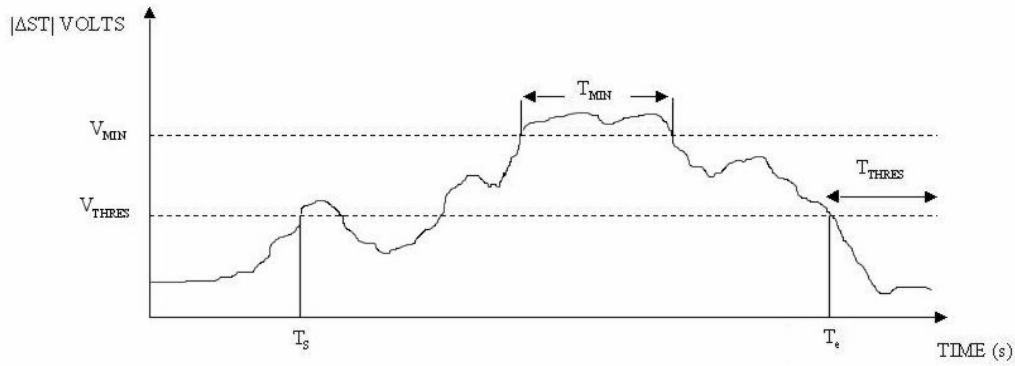
Figure 2. Illustration of amplitude thresholds and time intervals used in the algorithm.
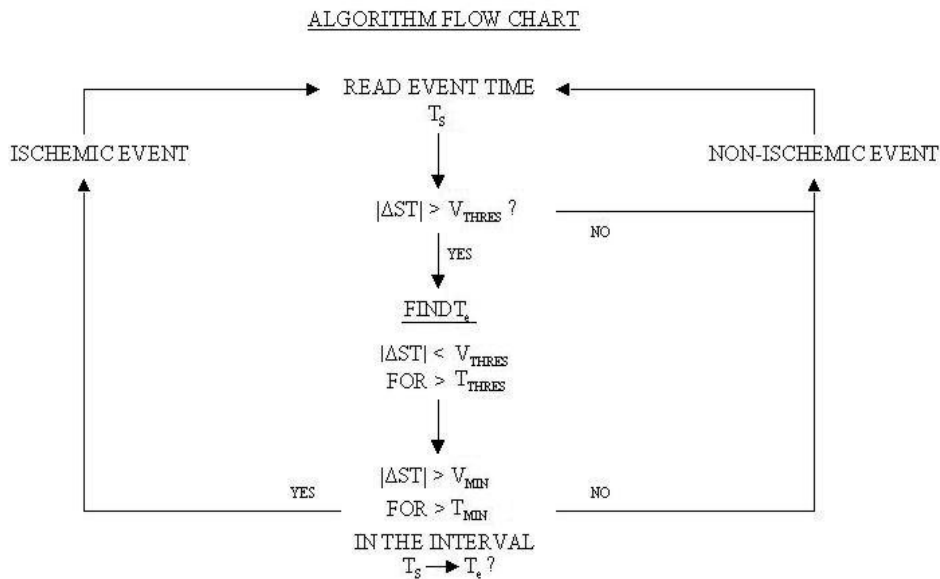
ALGORITHM FLOW CHART

Figure 3. Flow chart for automatic ischaemic event classification.

The end of an event (T_e) was defined as the time at which ΔST fell below the threshold for a further period of time (T_{thres}). Figure 2 defines the relevant ΔST and time thresholds. Figure 3 provides a flow chart for the automatic classification of events.

This basic algorithm gave results that were highly sensitive (identified nearly all ischaemic events) but not specific (many non-ischaemic events were classified as ischaemic), see section 3.1.

2.2. Algorithm optimization

With a view to optimizing the algorithm, we investigated the effect of reclassifying as non-ischaemic those events which were classified as ischaemic by the algorithm according to; i) the number of threshold crossings and ii) thresholds on the Mahalanobis distance from the first five principal components of the ST signals.

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2.2.1. Number of threshold crossings

We hypothesized that in ischaemia ST changes would occur rapidly with fewer crossings of the threshold voltage than artifactual ST changes. An additional parameter, the number of threshold level crossings (N_{cross}) for a specified threshold level (V_{cross}), was calculated for those events classified as ischaemic.

2.2.2. Principal component analysis

Principal component analysis of the ST time series has been reported to be more sensitive to ischaemic changes. Threshold levels were applied to the time series of the Mahalanobis distance from the first five principal components of the ST. For events classified as ischaemic by the basic algorithm, these events were reclassified as non-ischaemic if in the principal component time series the threshold level (V_{kltmin}) was not maintained for a period (T_{kltmin}).

2.3. Analysis

To evaluate the algorithms under different ΔST and time thresholds, the sensitivity, specificity, accuracy and challenge score (number of correct classifications – number of incorrect classifications (%)), were calculated.

3. Results

3.1. Basic algorithm

The results for altering the values of V_{min}, T_{min} and T_{thres} while keeping Vthres = 50 μV are shown in table 1. Figure 4 shows examples of ΔST for which correct and incorrect classifications were made.

Table 1: Results from the learning set to investigate the effect of altering three variables.

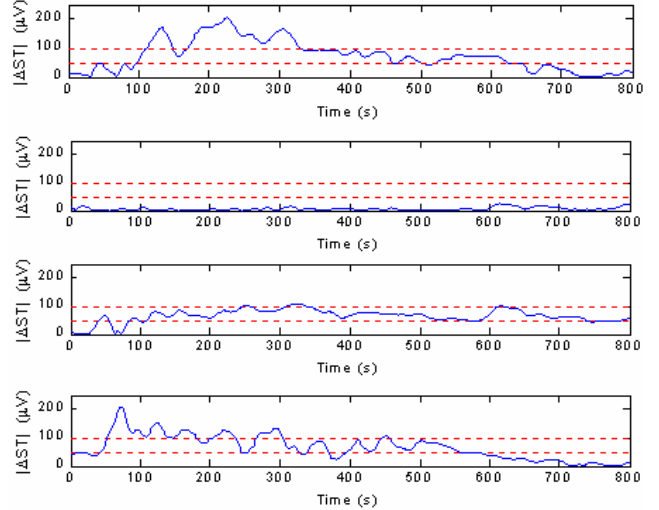| V_{min} (μV)	T_{min} (s)	T_{thres} (s)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Score (%)
100	30	40	99.0	88.8	91.1	82.3
110	30	40	85.6	91.0	89.8	79.6
100	34	40	94.3	89.8	90.8	81.6
100	30	36	99.0	88.8	91.1	82.3

Figure 4. Examples from top to bottom of a) ischaemic event (correctly classified), b) non-ischaemic event (correctly classified), c) ischaemic event classified as non-ischaemic, d) non-ischaemic event classified as ischaemic.

3.2. Number of threshold crossings

We maintained V_{thres}, V_{min}, T_{thres} and T_{min} at 50 μV, 100 μV, 40 s and 30 s respectively and investigated the effect of altering the threshold for N_{cross} when V_{cross} equaled 50μV and 100μV as shown in table 2 below.

Table 2: Results from the learning set to investigate the effect of altering N_{cross} at two different thresholds.

N_{cross}	V_{cross} (μV)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Score (%)
2	50	62.0	95.3	87.8	75.5
3	50	77.1	93.4	89.7	79.5
4	50	84.1	92.0	90.2	80.3
5	50	87.8	91.0	90.3	80.6
6	50	91.6	90.4	90.6	81.3
10	50	97.0	89.2	91.0	82.1
25	50	99.0	88.9	91.1	82.4
32	50	99.0	88.9	91.1	82.4
50	50	99.0	88.9	91.1	82.3
15	100	93.3	89.3	90.2	80.4
25	100	95.8	89.1	90.6	81.3
35	100	97.8	89.0	91.0	81.9

3.3.   Principal component analysis

Results for altering V_{kltmin} and T_{kltmin} with V_{thres}, V_{min}, T_{thres} and T_{min} maintained at 50 µV, 100 µV, 40 s and 30 s respectively are shown in table 3 below.

Table 3: Results from the learning set to investigate the effect of altering V_{kltmin} and T_{kltmin}.

V_{kltmin} (µV)	T_{kltmin} (s)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Score (%)
150	30	82.9	90.0	88.4	76.9
200	30	65.2	92.7	86.5	72.9
160	20	82.3	90.2	88.4	76.9

3.4.   Results with test data

Since none of the developments we performed increased sensitivity and specificity we submitted the basic algorithm with values for V_{thres}, V_{min}, T_{thres} and T_{min} at 50 µV, 100 µV, 40 s and 30 s respectively. We received a score of 81.4% and gained an accuracy of 90.7%.

4.   Discussion

An algorithm designed to accurately distinguish ischaemic and non-ischaemic ST changes has been developed and tested against expertly annotated reference data. Our algorithm achieved an accuracy of close to 91% for both the learning and test data sets (test data score 81.4%).

The basic algorithm was found to be sensitive but not specific leading us to investigate the effect of algorithm amplitude and time thresholds on accuracy and specificity for the learning data set. Here, a slight improvement in specificity (91% maximum) was obtained but at the cost of a marked reduction in sensitivity. A further enhancement to the algorithm then considered the number of threshold crossings and found that sensitivity and specificity values were a trade-off but the accuracy (and score) could not be improved significantly. Furthermore, the addition of the principal components from the ST measurements even slightly reduced the performance overall.

Our algorithm is simple to implement, intuitive, and straightforward to reproduce. The results demonstrate that the algorithm, based on the premise that ischaemic ST changes are large relative to non-ischaemic changes and that they are maintained for a period of time, is representative. We have shown the algorithm can reliably identify ischaemic ST changes in the ECG waveform.

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