Analysis of Transient ST Segment Changes During Ambulatory Monitoring Using the Karhunen-Loève Transform

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Abstract

We present an algorithm based on the Karhunen-Loève Transform (KLT) for robust automated detection of ischemic ST segment episodes and measurement of the duration of ischemia in two-channel ambulatory ECG data. The algorithm operates as a post-processor to an existing arrhythmia detector. The episode detector incorporates a single-scan trajectory recognition technique in the KLT feature space. The algorithm differentiates between true ischemic ST segment changes and non-ischemic ST deviations caused by axis shifts. In evaluations using the European Society of Cardiology ST-T Database, the algorithm achieved a gross ST episode sensitivity of 85.2%, with a positive predictivity of 86.2%; the gross ischemic ST duration sensitivity was 75.8%, with a positive predictivity of 78.0%.

1 Introduction

Automated detection and recognition of *ischemic ST changes* during *ambulatory ECG monitoring* is complicated by very slow drift of the ST segment level and more troublesome significant shifts of the ST level (>100 μV) caused by position-related changes in the electrical axis of the heart. Such *non-ischemic ST deviations* may cause false detection of ischemia, so an ST analyzer should identify these effects.

Using the *European Society of Cardiology ST-T Database* (ESC DB) [1], we have developed and evaluated a new two-channel algorithm based on the *Karhunen-Loève Transform*, for robust automated detection of transient ischemic and non-ischemic ST change episodes. For the evaluation we used performance measures and evaluation procedures published previously [2]. We extended the evaluation protocol to assess an analyzer's ability to differentiate between ischemic and non-ischemic ST change episodes.

2 Applying the KLT to the ECG

During an ischemic ST change episode the ST segment level plotted as a function of time typically varies smoothly, with a distinct peak. The morphology of the QRS complex is generally stable before, during, and after the ischemic episode. A typical non-ischemic ST change episode starts and/or ends with a significant axis shift, usually characterized by sudden changes in the ST segment level and in parameters describing QRS morphology (such as R-wave amplitude and projections of the mean electrical vector onto the lead axes). During axis shift all of these parameters change rapidly, generally over a period of 30 seconds or less, whereas the parameters are usually stable before and after the shift. If we observe the distribution of a large collection of ST segment *pattern vectors* for normal beats, we find that these pattern vectors usually form a single cluster. (In unusual cases, the presence of alternans may result in more than one cluster.) During ST change episodes, significant excursions of ST segment pattern vectors over the pattern space may be observed.

A pattern vector can be represented as a linear combination of KL basis functions; the components of such a *feature vector* are the KL coefficients. The KLT is optimal in the sense that the mean squared error obtained by approximating a given pattern of a random process using any given number of coefficients is minimized. For this reason, the residual error of a truncated KLT is an optimal estimate of noise content.

We derived two sets of KL basis functions: one from the data window covering the ST segment and initial portion of the T wave, and the other covering the PR interval and the QRS complex. Using the first set, ST segments may be represented as a sequence of feature vectors, which may be considered as samples of an *ST trajectory*. Similarly, we can use the second set to define a *QRS trajectory*, to obtain information about morphology changes in the QRS complexes. To derive the basis functions, we used all 90 records of the ESC

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DB. We used time-domain procedures [3] to exclude noisy beats and to estimate the isoelectric levels for the remaining 744,840 normal beats, which were used for the computation of the covariance matrices. Each set of KL basis functions is derived from 16 baseline-corrected samples of the ECG, taken at 8 ms intervals, for each of the two ECG leads. The samples used to derive the ST segment basis functions are those between FP+40 ms and FP+160 ms (where FP is ARISTOTLE's fiducial point); those used to derive the QRS complex basis functions occur during the interval from $FP - 96$ ms to $FP + 24$ ms.

3 Methods

The algorithm analyzes two ECG signals with reference to fiducial points and beat labels obtained from the annotation stream of the ARISTOTLE arrhythmia detector[4], written by the third author. Initially, signals are low-pass filtered (with a cutoff frequency of 55 Hz) by a 6-pole Butterworth filter. Baseline wander is removed using a cubic spline approximation technique. The single-scan algorithm excludes ectopic beats and their neighbors. Each normal beat is corrected to the isoelectric level[3], and is represented by the first five KL coefficients of each set of KL basis functions, resulting in one 5-dimensional feature vector for the ST segment, $\mathbf{s}(i)$, and another for the QRS complex, $\mathbf{q}(i)$ (where i is the beat number). All features are scaled by the corresponding eigenvalues such that their standard deviation ς is 1. The trajectory recognition algorithm analyzes the sequence of feature vectors, using the Mahalanobis distances (d; for KL vectors, the normalized Euclidean distances) between them to identify QRS and ST changes. We assume that the features are independent and normally distributed, so that d^2 is distributed as χ^2_N, i.e., as a chi-squared random variable with N (5) degrees of freedom. In the present case, the expected mean value, m, of d^2 is $N\varsigma^2 = 5$, and its expected standard deviation, σ, is $\sqrt{2N}\varsigma^2 \approx 3.16$.

3.1 Noise detection

Noisy beats must be excluded from analysis. The KL representations of noisy beats may be expected to have relatively large residual errors, and to differ markedly from those of neighboring beats. Based on these observations, the algorithm considers beat i as noisy if the normalized residual error for the ST segment, or for the QRS complex, exceeds 25%, or if the ST or QRS feature vector differs sufficiently from those of the past few beats:

$$d^2(\mathbf{q}(i), \tilde{\mathbf{q}}(i)) > \Theta \ \bigvee \ d^2(\mathbf{s}(i), \tilde{\mathbf{s}}(i)) > \Theta$$

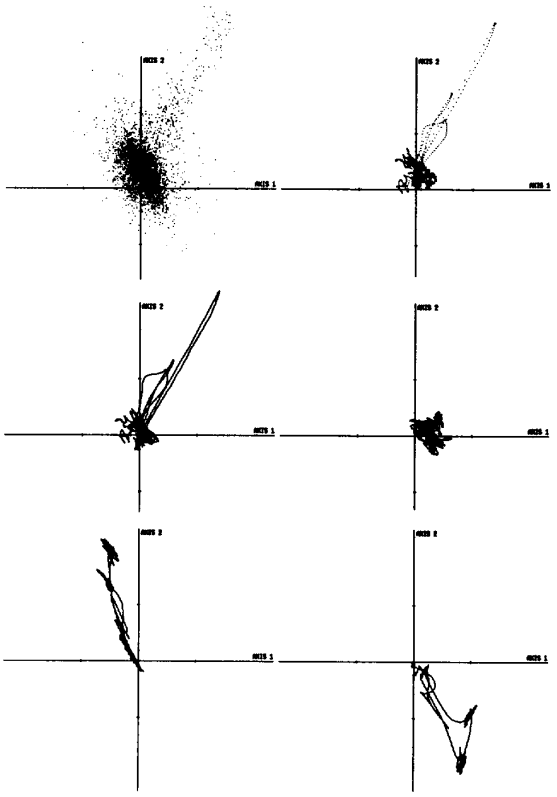

Figure 1: Feature trajectories (axes are the first two KL coefficients): ST trajectory for record e0104 (including three ischemic ST episodes) after exclusion of noisy beats (upper left), after resampling and smoothing (upper right), after correction of the reference ST level (center left); QRS complex trajectory for record e0104 after exclusion of noisy beats, resampling and smoothing (center right); ST trajectory for record e0509 (including one non-ischemic ST episode) after exclusion of noisy beats, resampling and smoothing (lower left); QRS trajectory for record e0509 after exclusion of noisy beats, resampling and smoothing (lower right).

where $\tilde{\mathbf{q}}(i)$ and $\tilde{\mathbf{s}}(i)$ are the mean feature vectors for the last 15 normal beats, and Θ is a distance threshold (8.16, i.e., $m{+}1{\cdot}\sigma$).

3.2 Detection of axis shifts

After exclusion of noisy beats, sequences of the feature vectors are smoothed (using a 15 point moving average), resampled at a constant rate of 0.5 Hz, and further smoothed (using a 9 point moving average). Figure 1 shows examples of the feature trajectories after resampling and smoothing. In the absence of QRS or ST changes, the feature vectors are confined to a small

volume of the feature space. During an ST change episode, the ST trajectory moves continuously through a larger volume. During non-ischemic episodes, both the QRS and ST trajectories move in stepwise fashion, but remain confined to small volumes at other times. The axis shift detection logic searches for step changes in the QRS and ST *distance functions*, defined as:

$$F_q(k) = d(\mathbf{q}(k), \mathbf{q}(1))$$
$$F_s(k) = d(\mathbf{s}(k), \mathbf{s}(1))$$

where k is the sample number (in the resampled sequence), and $\mathbf{q}(1)$ and $\mathbf{s}(1)$ are the first QRS and ST feature vectors. A step change in either function is characterized by an interval during which the function is approximately constant (its mean absolute deviation from its mean value must be less than 0.33 over an interval of 224 seconds), followed by an interval during which it changes significantly (the 74-second moving average value must change by at least 1.11 within the next 74 seconds), followed by an interval during which the function is again approximately constant (defined as for the first interval). The thresholds were estimated empirically, from trend plots of the functions.

3.3 Correction of the reference ST level

Correction of the reference ST segment level to account for very slow drift of the ST segment level is performed by updating the mean feature vector, $\bar{\mathbf{s}}(k)$, of "normal" ST segments. A tentative new value, S, for the mean feature vector, is determined as an exponentially weighted sum of its current value and the current feature vector, $\mathbf{s}(k+1)$:

$$S = \frac{1}{\alpha} \cdot ((\alpha - 1)\bar{\mathbf{s}}(k) + \mathbf{s}(k+1))$$

where the time constant $\alpha = 450$ (15 minutes). If S is sufficiently close to the first feature vector, i.e.,

$$d^2(S, \mathbf{s}(1)) < \Psi$$

and the current feature vector is close to the current mean, or closer to the first feature vector, $\mathbf{s}(1)$, than is the current mean:

$$d^2(\mathbf{s}(k+1), \bar{\mathbf{s}}(k)) \leq \Phi \bigvee$$
$$d^2(\mathbf{s}(k+1), \mathbf{s}(1)) < d^2(\bar{\mathbf{s}}(k), \mathbf{s}(1))$$

then the new mean, $\bar{\mathbf{s}}(k+1)$, is taken to be S; otherwise it is left unchanged. An example of updating the mean feature vector may be seen in Figure 1. The thresholds Ψ and Φ were determined empirically: $\Psi = 11.32$ $(m + 2\sigma)$, and $\Phi = 1.02$ $((m + \sigma)/8)$. Whenever the squared ST distance function, F_s^2, exceeds $m + 3\sigma$ or $m + 9\sigma$, Φ is increased for the following 30 minutes, to 3.62 $((m + 3\sigma)/4)$ or to 8.36 $((m + 9\sigma)/4)$, respectively.

3.4 Detection of ST episodes

ST episodes are identified by analysis of the corrected ST segment distance function:

$$C_s(k) = d(\mathbf{s}(k), \bar{\mathbf{s}}(k))$$

Each sample of C_s is classified as normal or abnormal, using decision thresholds that incorporate a guard zone[5]. Sequences of abnormal samples form ST episodes. Any sample below the fixed lower bound of the guard zone, Λ_l, is classified as normal. Similarly, any sample above the adaptive upper bound of the guard zone, Λ_u, is classified as abnormal. We defined three additional adaptive thresholds for classifying samples within the guard zone. The first, $L(k)$, is defined as an exponentially weighted average of the corrected ST segment distance function:

$$L(k) = \frac{1}{\beta}((\beta - 1)L(k-1) + C_s(k))$$

where the time constant $\beta = 450$ (15 minutes); the second threshold, $U(k)$, is defined as $2 \cdot L(k)$; and the third threshold, Λ_c, is the center of the guard zone $((\Lambda_{u_0} + \Lambda_l)/2)$. The width of the guard zone is adaptive. Whenever $L(k) > \Lambda_c$ and $C_s(k) > 3\Lambda_c$, the upper bound, Λ_u, is reset to $\Lambda_{u_0} + \Lambda_c$. Whenever $U(k) < \Lambda_c$, then Λ_u is restored to its initial value, Λ_{u_0}. By study of receiver operating characteristics for the ischemic episode sensitivity and the ischemic episode positive predictivity derived by varying Λ_l and Λ_{u_0}, we obtained values of 1.30 and 1.62 for these parameters. To define the onset and end of each detected episode, we applied the timing criteria used by the human annotators of the ESC DB[1].

If an interval of detected axis shift coincides with the onset or the end of a detected episode, and the amplitude of the extreme ST deviation for the episode in any ECG lead does not exceed 300μV, the algorithm labels it as a non-ischemic ST episode; otherwise, the episode is considered to be ischemic.

4 Evaluation

The sensitivity matrix (Table 1) summarizes how the reference ischemic and non-ischemic ST episodes were labelled by the algorithm, while the positive predictivity matrix (Table 1) summarizes how the detected ischemic and non-ischemic ST episodes were labelled in the reference annotations. To be counted as true positive each reference annotated episode as well as detector annotated episode has to satisfy the "matching" test. Matching of given episode occurs when the period of overlap (i.e., the interval in which both the reference and the detector annotations indicate that an

Se matrix		*Algorithm*		
		Ischemic	*Non-isc*	*No dev*
Ref.	*Ischemic*	213 (*a*)	3 (*b*)	34 (*c*)
	Non-isc	2 (*d*)	7 (*e*)	0 (*f*)
	No dev	–	–	–

+*P* matrix		*Algorithm*		
		Ischemic	*Non-isc*	*No dev*
Ref.	*Ischemic*	206 (*g*)	3 (*h*)	–
	Non-isc	2 (*i*)	6 (*j*)	–
	No dev	31 (*k*)	6 (*l*)	–

Table 1: Ischemic episode sensitivity (Se) matrix (above) and positive predictivity ($+P$) matrix (below) for the KLT-based ischemia detector, on the ESC Database.

ST change episode is in progress) includes the extrema of the episode under the test, or when at least 50% of the length of the episode is overlaped by the ischemic or by the non-ischemic episode. Given an episode labelled by the reference or by the analyzer's annotations, and satisfying the matching test, is counted as ischemic if the extrema of the episode is overlaped by the episode of type ischemic or if the episode is overlaped at least 50% by the episode of type ischemic. Failing this criteria the episode, satisfying the matching test, is counted as non-ischemic. Considering all ST change episodes as episodes of single type yields: $TP_S = a+b+d+e = 225$, $FN = c+f = 34$, $TP_P = g+h+i+j = 217$, and $FP = k+l = 37$. Since the events of clinical interest are ischemic ST episodes, we furthermore consider all non-ischemic episodes as non-events. Following this consideration our algorithm obtained for the entire ESC Database: $TP_S = a = 213$, $FN = b+c = 37$, $TP_P = g = 206$, and $FP = i+k = 33$. Table 2 presents statistics for detection of ischemic ST episodes and measurement of the duration of ischemia, as defined by the AAMI; the bracketed figures in Table 2 are estimated lower bounds on these statistics, based on 10,000 bootstrap trials.

Comparing the algorithm's measurements of ST deviation with the 368 reference measurements in the database (corresponding to the ST episode extrema in each lead), the mean difference between the algorithm and the reference measurements was 17.8 μV, with a standard deviation of 61.8 μV, and a correlation coefficient of 0.972; 10.9% (40/368) of the algorithm's measurements differed from the reference measurements by more than 100 μV.

	IE Se	*IE +P*	*ID Se*	*ID +P*
Gross	85.2% (80.6%)	86.2% (81.1%)	75.8% (69.6%)	78.0% (72.5%)
Average	87.1% (82.2%)	87.7% (82.9%)	78.2% (73.2%)	74.1% (69.3%)

Table 2: AAMI-defined performance statistics for the KLT-based ischemia detector on the ESC Database (IE: ischemic episode – each ischemic episode weighted equally, ID: ischemic duration – each ischemic minute weighted equally). The bracketed figures are 5% confidence limits (see text).

5 Discussion

We compared the performance of the KLT-based algorithm to an otherwise identical algorithm which uses time domain features for noise detection and construction of the sequence of average beats[3]. The earlier algorithm represents the ST segment by two features (ST segment level at the point FP+120ms for each ECG lead), and the QRS complex by projections of the mean electrical vector onto the lead axes; its gross ischemic episode Se (82.4%) and +P (83.4%), and gross ischemic duration Se (72.5%) and +P (78.5%) were all bettered by the KLT-based algorithm, by small but significant amounts (as determined by bootstrap estimation). Thus the KLT-based algorithm appears effective in rejecting noise and retaining useful information necessary for analysis.

References

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