Towards the Prediction of Transient ST Changes

RJ Povinelli

Marquette University, WI, USA

Abstract

This paper studies the ECG signal prior to a transient ST change. Two hypotheses are proposed. The first is that various types of ST changes can be differentiated using the signal just prior to the ST event. The second is that ischemic ST changes can be differentiated from non-events, again using the signal prior to the ST event. A machine learning approach, based on Gaussian Mixture Models and maximum likelihood Bayesian classification, is used to analyze the ECG signal. Two sets of feature extraction techniques, reconstructed phase space and Karhunen Lòeve transform, are applied, both of which capture morphological characteristics of the ECG signal. The results in addressing the first hypothesis show that information indicative of the type of ST change is present in the signal prior to the onset of the ST event; however the classification accuracy is low. The second hypothesis cannot be affirmed with the results presented here.

1. Introduction

This paper is an entry in the 2005 Computers in Cardiology challenge, which is to revisit the datasets from the previous five challenges with the goal of presenting new discoveries using these previous datasets. This study extends the 2003 challenge by studying characteristics of the ECG signal before the onset of transient ST changes. Two hypotheses are proposed. The first is that different types of ST changes (ischemic, heart rate, conduction change, and axis shift) can be differentiated using the ECG signal before the ST event. The second hypothesis is that ischemic ST episodes can be differentiated from non-ST events, again using the ECG signal before the ST event or non-event.

To address the first hypothesis, we classify the ST events as labeled in the Long Term ST (LTST) database, using the 30s of ECG signal just prior to the start of an event. To address the second hypothesis, a randomly generated second set of non-events is created. We classify non-events and ischemic events.

To test these hypotheses, we study two methods for characterizing the ST segment and T-wave shape. The first is a dynamical systems approach based on reconstructed phase spaces (RPSs) [1], and the second is based on the Karhunen Lòeve Transform (KLT) of the ST segment, which is provided with the LTST dataset. A Bayesian classifier over a Gaussian Mixture Model (GMM) of these features is the machine learner for creating an automatic classifier of the events.

Beyond our intrinsic interest in solving difficult classification/prediction problems, the question of clinical relevance must be addressed for such a study. The clinical relevance begins with an acknowledgement of the prevalence, cost of detection, and complications due to undetected myocardial ischemia. Myocardial ischemia is the most common heart disease and is caused by a blockage in the cardiac arteries [2], which deprives the cardiac tissue of necessary oxygen, and, if not reversed, leads to a myocardial infraction. Common methods for detection, such as coronary angiography are costly and invasive.

Thus, an effective, low-cost, automatic screen based on the analysis of ECG Holter recordings would be of clinical relevance. This argument justifies the study of ST episodes, which can be caused by the "injury current" due to the differences in conduction between ischemic and healthy cardiac tissue. But why study the ECG signal before the identified ST episode? We see three answers to this question. First, a greater understanding of the signal before the onset of the ischemia may provide insight into the signal after the onset. Second, understanding the signal before the onset will help in differentiating non-ischemic ECG signals from ischemic ECG signals. Third, if effective automatic methods could be developed for predicting the onset of ischemia, this would enable preventative and timely automatic therapies to be provided, such as might be delivered by a drug pump.

Examples of work in studying changes in the ST level include Langley et al. [3], which uses threshold levels and time durations to classify ischemic events; Diamantras et al. [4], which uses a neural network to extract nonlinear principle components of the ST segment and a Mahalanobis distance based classifier; Silipo et al.[5], which compares traditional ECG classification methods with artificial neural network based approaches; and Zimmerman et al. [6, 7], which uses RPSs, GMMs, and support vector machines to distinguish ischemic and non-ischemic ST changes.

The rest of the paper is organized as follows: A

0276−6547/05 $20.00 © 2005 IEEE

Computers in Cardiology 2005;32:663−666.

discussion of the LTST dataset is presented. Next, an overview of the methods is provided. The following section presents the results. The paper concludes with a summary and discussion of the results.

2. Long-term ST database

This study uses the LTST database, which consists of 86 long term (21 to 24 hour) Holter ECG recordings. The free portion of the dataset consists of 43 records from 42 patients (1772 events using the B protocol) and is used as the training set for this study. The fee portion of the dataset consists of 43 recordings from 38 patients (1974 events using the B protocol) and is used as the test set for this study [8, 9]. A second partitioning of the dataset is formed for the purposes of ten-fold cross validation. The partitions are formed so that no patient is in more than one fold, i.e. the results are patient independent. The first five folds are formed from the training set with records assigned to folds in sequential order according to the record numbers. The first three folds contain nine records each and the next two folds contain eight records each. The last five folds are formed from the test set using the same procedure.

The J-point annotations provided in the dataset are used, as are the ischemic, axis shift, conduction change, and heart rate related ST change labels. The five KLT coefficients of the ST segments provided with the dataset also are used.

An additional set of non-events is generated randomly according to a uniform probability distribution across records that had ischemic events and in equal number to the number of ischemic events in that record, subject to the provision that a non-event is not within five minutes of the beginning of the record or within five minutes of the beginning or end of any labeled event or episode.

3. Methods

We present two methods for characterizing the ECG signal before the ST event. The two methods share a common machine learning approach, which is a GMM to statistically characterize an underlying distribution of features and a Bayesian maximum likelihood classifier. The difference between the two approaches is found in their features sets. The first approach constructs RPSs of the ST segment and T-wave and then uses the GMM to model the structure of the resultant spaces. The second approach uses the KLT of the ST segments to generate a five dimensional representation of the ST segment. A GMM is then learned over the resulting space.

A common element between the two approaches is GMMs, which take the form of

$$p(\mathbf{x}) = \sum_{m=1}^{M} w_m p_m(\mathbf{x}) = \sum_{m=1}^{M} w_m \mathcal{N}(\mathbf{x}; \boldsymbol{\mu}_m, \boldsymbol{\Sigma}_m),$$

where $\mathbf{x}$ is the feature vector, M is the number of mixtures, $\mathcal{N}(\mathbf{x}; \boldsymbol{\mu}_m, \boldsymbol{\Sigma}_m)$ is a normal distribution with mean $\boldsymbol{\mu}_m$ and covariance matrix $\boldsymbol{\Sigma}_m$, and w_m is the mixture weight, with the constraint that the weights sum to unity. The GMM is estimated using Expectation-Maximization (EM). The second common element is a Bayesian maximum likelihood classifier, which takes the form

$$p(\mathbf{X} \mid c_i) = \prod_{n=1}^{N} p(\mathbf{x}_n \mid c_i)$$

$$\hat{c} = \arg\max_i \, p(\mathbf{X} \mid c_i),$$

where $\mathbf{x}_n$ is the n^{th} feature vector, $\mathbf{X}$ is the set of all feature vectors, and c_i is the i^{th} class.

The essence of the GMM/RPS approach is to transform extracted ST segments and T-waves into RPSs and learn GMMs over the resultant RPSs. Multiple sets of GMMs are learned – one set for each ST event class. The set associated with a given class corresponds to models associated with the J-points found in the 30s of ECG signal before the event.

Given a time series $x = x_n$, $n = 1, ..., N$, a sequence of state variable observations, a point in a RPS is

$$\mathbf{x}_n = \left[x_{n-(d-1)\tau} \quad \ldots \quad x_{n-\tau} \quad x_n \right],$$

where $n = (1 + (d-1)\tau), ..., N$, d is the dimension of the RPS, and τ is the time lag. When constructed with a large enough dimension, the resulting structure has a one-to-one correspondence with the state structure of the underlying generating system [10].

To model the changes in ST segments and T-waves, all J-points 30s before the signal are identified and the corresponding signals transformed into RPSs. Each J-point is indexed, and a signal 400ms long starting at the J-point is extracted. The RPSs associated with a particular index and ST event class are combined to form a large RPS associated with each index. A 16 mixture GMM is then learned for each combined RPS. The dimension and lag for the RPS are determined using heuristic methods based on the false nearest neighbors and the first minimum of the automutual information. See [1] for more details on this process.

Test ECG signals go through the same process to extract the ST segments and T-waves associated with each J-point 30s before the event. The extracted signals are then transformed into RPSs. The likelihood of each RPS for each class is computed using the GMM. The likelihoods associated with each J-point are combined to yield a cumulative likelihood that is used in the Bayes maximum likelihood classifier to yield a classification.

The GMM/KLT approach is similar in structure to the GMM/RPS approach. The KLT coefficients for the ST segments for the ECG 30s before the event are extracted and 16 mixture GMMs are learned over these extracted

KLTs. Multiple sets of GMMs are learned – one set for each ST event class. The set associated with a given class corresponds to models associated with the KLTs found in the 30s of ECG signal before the event. The details of the KLT formation are found in [9, 11].

Test ECG signals go through the same process to extract the KLTs associated with the ST segments 30s before the event. The likelihoods of all KLTs for each class are computed using the GMMs. The likelihoods associated with each KTL extracted from the 30s ECG are combined to yield a cumulative likelihood which is used in the Bayes maximum likelihood classifier.

4. Results

This section presents results from applying the RPS/GMM and KLT/GMM approaches discussed above to classifying ischemic, rate related, axis shift, and conduction change events using the ECG signals 30s before the event, as well as the results from applying the RPS/GMM and KLT/GMM approaches to differentiating ischemic and non-events.

4.1. Distinguishing events

The results from distinguishing different ST change events are given in Tables 1-4. Table 1 provides the confusion matrix for the test set results of the RPS/GMM approach.

Table 1. Test set confusion matrix for classifying ischemic (is), rate related (rt), axis shift (as), and conduction change (cc) using the RPS/GMM approach.

	is	rt	as	cc
Is	309	2	379	33
Rt	26	1	63	2
As	207	7	470	21
Cc	0	3	450	1

The expertly labeled classification is given by the labels in the first column of Table 1. The algorithm determined classification is given by the labels in the first row of Table 1. This scheme is used for all confusion matrices in this paper, as are the labels is, rt, as, cc, which correspond to ischemic, rate related, axis shift, and conduction change, respectively.

The classification accuracy is 39.6% vs. 25.0% for chance. The sensitivity for ischemia is 42.7%. The specificity for other events is 81.4%. Applying the χ^2 test, the above confusion matrix is different from one generated by a random classifier (Type I error $p < 10^{-15}$). Table 2 shows the confusion matrix for the ten-fold cross validation, using the folds described above.

Table 2. 10-fold cross validation confusion matrix for ischemic (is), rate related (rt), axis shift (as), and conduction change (cc) using the RPS/GMM approach.

	is	rt	as	cc
is	166	15	892	53
rt	33	0	191	8
as	122	7	1313	51
cc	163	2	692	38

The classification accuracy is 40.5% vs. 25.0% for chance. The sensitivity for ischemia is 14.7%. The specificity for other events is 87.9%. Applying the χ^2 test, the above confusion matrix is different from one generated by a random classifier (Type I error $p < 10^{-15}$). The accuracies averaged across folds is 43.7% with a standard deviation of 25.3%. This differs slightly from the combined confusion matrix accuracy as this accuracy is calculated on each fold before averaging. This allows an estimate of the standard deviation of the accuracy to be generated. Based on the t-test, the accuracy of the RPS/GMM approach is greater than chance (Type I error of $p = 0.02$). Table 3 presents the confusion matrix for the test set results of the KLT/GMM approach.

Table 3. Test set confusion matrix for classifying ischemic (is), rate related (rt), axis shift (as), and conduction change (cc) using the KLT/GMM approach.

	is	rt	as	cc
is	301	10	412	0
rt	28	10	52	2
as	310	27	366	2
cc	6	0	448	0

The classification accuracy is 34.3% vs. 25.0% for chance. The sensitivity for ischemia is 41.6%. The specificity for other events is 72.5%. Applying the χ^2 test, the above confusion matrix is different from one generated by a random classifier (Type I error $p < 10^{-15}$).

A ten-fold cross validation also was performed using the folds discussed above. Table 4 shows the confusion matrix. The classification accuracy is 33.2% vs. 25.0% for chance. The sensitivity for ischemia is 42.3%. The specificity for other events is 55.6%. Applying the χ^2 test, the above confusion matrix is different from one generated by a random classifier (Type I error $p < 10^{-15}$). The accuracies averaged across folds is 39.3% with a standard deviation of 18.6%. Based on the t-test, the accuracy of the KLT/GMM approach is greater than chance (Type I error of $p = 0.02$).

Table 4. 10-fold cross validation confusion matrix for ischemic (is), rate related (rt), axis shift (as), and conduction change (cc) using the KLT/GMM approach.

	Is	rt	as	cc
is	476	72	578	0
rt	66	59	105	2
as	678	102	710	3
cc	420	0	475	0

A comparison of the 10-fold cross validation accuracies of the RPS and KLT approaches using the one-tailed t-test yields that the RPS accuracy is greater than the KLT with p = 0.66, which indicates that they are not statistically different.

4.2. Distinguishing non-events from events

The results for both approaches for distinguishing non-events from events are not statistically different from chance. Using a ten-fold cross validation, the RPS/GMM combined accuracy is 50.3% with chance being 50.0%. The sensitivity for ischemia is 2.0%. The specificity for other events is 98.5%. The 10-fold average accuracy is 50.7% with a standard deviation of 1.9%. This is greater than chance with a Type I error of p = .53, indicating that the RPS/GMM method is not statistically different from chance on this task.

Similarly, the ten-fold cross validation combined accuracy is 54.0% with chance being 50%. The sensitivity for ischemia is 74.6%. The specificity for other events is 33.5%. The 10-fold average accuracy is 53.1% with a standard deviation of 5.7%. This is greater than chance with a Type I error of p = 0.13, indicating that the KLT/GMM method is not statistically different from chance on this task.

A comparison of the 10-fold cross validation results between the RPS and KLT methods using the one-tailed t-test yields that the KLT accuracy is greater than the RPS accuracy with p = 0.20, which indicates that they are not statistically different.

5. Discussion and conclusions

The results found in this study in many cases were statistically significant, but not as substantial as hoped for. For example, the accuracy for distinguishing between ischemic, rate related, axis shift, and conduction change ST events is significantly above chance for both the RPS/GMM and KLT/GMM approaches, but certainly not at a level that would be called effective. On the other hand, this result clearly indicates that some information is contained in the ECG signal before an ST event that is predictive of that ST event.

The second hypothesis that ischemic ST episodes can be differentiated from non-ST events, using the ECG signal before the ST event or non-event, cannot be supported by the results found in this study. Both machine learning methods had accuracies that were not significantly different than chance.

References

[1] Povinelli RJ, Johnson MT, Lindgren AC, Ye J. Time series classification using Gaussian mixture models of reconstructed phase spaces. IEEE Transactions on Knowledge and Data Engineering 2004;16:779-783.

[2] Preventing heart disease and stroke: Centers for Disease Control and Prevention, 2004.

[3] Langley P, Bowers E, J Wild MD, et al. An algorithm to distinguish ischaemic and non-ischaemic ST changes in the Holter ECG, Computers in Cardiology, Thessaloniki, Greece, 2003;30:239-242.

[4] Diamantaras KI, Stamkopoulos T, Maglaveras N, Strintzis M. ST segment nonlinear principal component analysis for ischemia detection, Computers in Cardiology, Indianapolis, IN, 1996;23:493-496.

[5] Silipo R, Marchesi C. Artificial neural networks for automatic ECG analysis. IEEE Transactions on Signal Processing 1998;46:1417-1425.

[6] Zimmerman MW, Povinelli RJ, Johnson MT, Ropella KM. A reconstructed phase space approach for distinguishing ischemic from non-ischemic ST changes using Holter ECG data, Computers in Cardiology, Thessaloniki, Greece, 2003:243-246.

[7] Zimmerman MW, Povinelli RJ. On improving the classification of myocardial ischemia using Holter ECG data, Computers in Cardiology, Chicago, Illinois, 2004:377- 380.

[8] Computers in cardiology challenges. Vol. 2003. Cambridge, MA, 2003.

[9] Jager F, Taddei A, Moody G, et al. Long-term ST database: A reference for the development and evaluation of automated ischaemia detectors and for the study of the dynamics of myocardial ischaemia. Medical and Biological Engineering and Computing 2003;41:172-182.

[10] Takens F. Detecting strange attractors in turbulence. In: Mathematics Institute, University of Warwick, Dynamical Systems and Turbulence, Warwick, 1980;898:366-381.

[11] Jager F, Mark RG, Moody GB, Divjak S. Analysis of transient ST segment changes during ambulatory ECG monitoring using the Karhunen Lòeve transform, Computers in Cardiology, 1992:691–694.

Address for correspondence

Richard J. Povinelli
EECE Department, Marquette University
1515 W. Wisconsin Ave.
Milwaukee, WI 53233
richard.povinelli@marquette.edu