ST-T Segment Change Recognition using Artificial Neural Networks and Principal Component Analysis

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Abstract

Any ST-T segment was here represented by using the Principal Component Analysis, or Karhunen-Loève Transform (KLT). A representative KL basis set was built from a database containing more than 97000 normal and abnormal ST-T segments. So it was possible to concentrate the 90% of the ST-T signal energy in the first KL coefficients. For the evaluation, the ST-T European Database was chosen, because of its large amount of ischemic episodes. The baseline was removed by using a cubic spline and an adaptive filter was applied in order to improve the signal-to-noise ratio in the final KL series, delivering an improvement of about 10 dB. Then a 3-layers feedforward neural network, trained with Back Propagation, was applied to the KL series to recognize ST-T level changes. Each input pattern consisted of 28 features, representing 7 ST-T segments, each one described by means of its first 4 KL coefficients. 3 output units were designed, one to describe ST depression, one ST elevation, and one to represent artefacts. The use of Principal Component Analysis and of Artificial Neural Networks allowed us to obtain a sensitivity of 77% and a Positive Predicitive Accuracy of 86% on the test set.

1. Introduction

Analysis of long term ECG represents a significant diagnostic tool for early detection and therapeutic control of several cardiac diseases. Myocardial ischemia, as evidenced by the alteration of the ventricular repolarization waveform of the ECG, is particularly important, because of the associated potential complication of myocardial infarction as well as for the large amount of subjects at risk.

Ischemic changes of the ECG generally affect the entire repolarization wave shape and are inadequately characterized by isolated features, such as a few measurements of the ST segment amplitude changes, even if these are obtained as an average of several signal samples. Whereas in the last years some algorithms have been developed, they are not sufficiently reliable yet, because of the artefacts and of the slowly ST change phenomenon in ECG measure trends. The artefacts, produced by any electrical cardiac axis shift, for example due to a postural change of the patient, can be easily confused with ischemic ST changes. On the other hand, sometimes the slow ST evolution does not allow the detection of the weakest episodes, while early diagnosis and treatment can prevent a sudden death due to infarction.

In order to improve the sensitivity value in automatic recognition of ischemic ST level changes, we used the Principal Component Analysis, or Karhunen-Loève Transform for the ECG signal transformation and an Artificial Neural Network for the ST-T change detection.

This combination of Principal Component Analysis and of Neural Classification allowed us to obtain good results (80% around of sensitivity and PPA on the test set), better than those obtained by commercial system and comparable with physician's performance on the same ST database we used.

2. Principal component analysis or Karhunen-Loève transform (KLT)

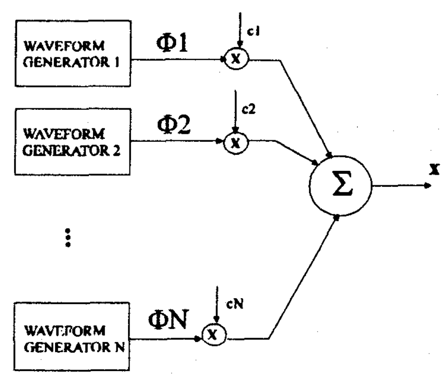

Figure 1. Reconstruction of a pattern **x** with KL basis Φ_i.

The KL Transform is a transformation of the current coordinate system in a new one more able to represent a given input space. It describes the original vectors according to the directions of maximum information in the training set, derived from the data covariance matrix. In fact, the orthogonal eigenvectors of the covariance matrix are chosen as basis functions, Φ_k, to perform the KLT, and the corresponding eigenvalues, λ_k, represent the average dispersion of the projection of input vectors onto the corresponding basis functions. If the eigenvectors are sorted in order by their respective eigenvalues such that λ_k is greater than λ_{k+1}, the corresponding basis functions Φ_k are arranged in order of representational strength. If the mean vector **m** is zero, the eigenvalue λ_k of the covariance matrix represents the average energy of the projection of input vectors onto the associated basis function Φ_k, instead of its average dispersion. The reconstruction process of a vector $\mathbf{x}$ by using the KL basis functions is shown in figure 1.

We chose to represent the ECG signal with the KL transform, because in that way it is possible to recover maximum information from any pattern $\mathbf{x}$ by using only the most representative basis functions Φ_k, associated to the highest eigenvalues λ_k, and then for a given set of basis waveforms a minimum number of KL coefficients are necessary.

3. KL basis functions

To obtain a representative training set of normal and abnormal ST-T waveforms, we selected 105 fifteen-minutes ECG records. For each QRS complex, detected and labeled by using ARISTOTLE software, the ST-T segment was defined as the vector of samples beginning 85 ms following the R peak and ending 240 ms prior to the next R peak. If the RR parameter, defined as the interval between two following R peaks, was less than 720 ms, the end of the window was located at 2/3 of the way from the initial R peak to the following one.

To avoid the effects of ectopic and other abnormal beats, we accepted only ST-T segments placed between two QRS complexes labeled as normal by ARISTOTLE. We estimated the isoelectric level as the average signal value during the 20 ms interval, beginning 80 ms prior to the R peak. Beats, for which the estimated isoelectric level was different by more than 0.2 mV from that of the previous or of the following beat, were excluded from the training set. We then manually rejected a small number of ST-T patterns, that we judged subjectively to be particularly noisy. The remaining 97663 ST-T patterns constituted the training set [1].

We corrected also those beats for baseline variation, using cubic splines and a high pass filter. Moreover the effects of heart rate on ST-T segment can be corrected by using the Bazett's formula, that within the ST-T window resamples the ECG signal at the original sampling frequency (250 Hz) divided by the square root of the previous RR interval, that is:

$$STTc(t*) = STT\left(\frac{t}{\sqrt{RR_{i-1}}}\right).$$

From the described training set, we obtained the KL basis functions, the first ones of which are shown in figure 2. The solid lines show basis functions derived without Bazett's correction, while the dashed lines show basis functions derived with Bazett's correction. We have got that this representation permits about the 90% of the ST-T signal energy to be represented by the first 4 KL coefficients. Since most heart rates exceed 60 beat/minute, the correction was applied to the most ST-T segments and tended to stretch them.

The first basis function, and to a lesser extent the second one, represents the dominant low frequency components of the ST-T segment, concentrated in the first 400 ms after the QRS. The next few basis functions contain more high frequency energy, and contain energy more evenly distributed across the entire ST-T segment. These functions represent components being in abnormally prolonged ST-T segments and in U waves, when they happen to be within the time window. The remaining higher order basis vectors contain almost exclusively high frequency content related to noise in the training set. Then by inspection of these basis vectors, we could predict that the first two KL coefficients should be already a good tool for detecting ischemic ST-T changes, since they contain virtually all of the low frequency energy.

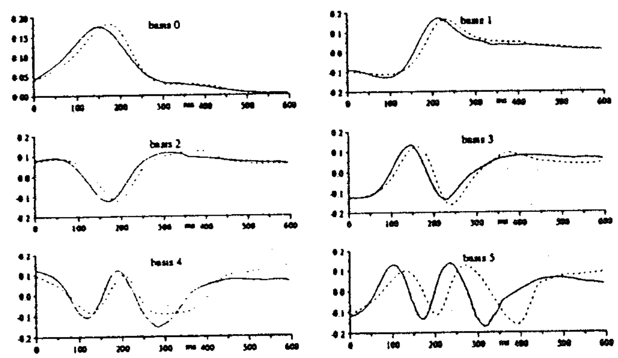

Figure 2. KL basis functions set.

4. KL series

For the evaluation we used the European Society of Cardiology ST-T database, containing 100 ECG annotated records, sampled at 250 samples/s and lasting 2 hours each one. That was chosen because of its large amount of annotated ischemic ST-T episodes.

We performed several experiments for observing the correctness of the ST-T segment reconstructions [1] and 4 KL coefficients were chosen to represent our data, because they were supposed to be sufficient to reconstruct the most ST-T segments in the test set. So the ST-T dynamics was characterized by the study of 4 KL coefficient time series. We assigned to each QRS fiducial point the KL coefficients extracted from the corresponding ST-T segment, by means of its inner product with the KL basis functions. If the ST-T segment had no as many components as the basis functions had, it was corrected with the zero-padding technique. A cubic spline baseline removal was applied to every ST-T segment.

Further noise in the KL time series was reduced using an adaptive filter that removed noise uncorrelated with the ST-T segment. In fact, an adaptive estimation of quasi-periodic signal, such as the ST-T segment, permits reduction of noise uncorrelated with the signal, with attendant improvements in the ability to track subtle dynamics variations in these signals. The designed adaptive filter made use of the recurring features of the signal and it was based on an adaptive linear combiner.

Here we present the results of estimating and monitoring the KL series on some ECG records from European ST-T database.

The first figure reports the time series for the first and the second lead of e0103 record, obtained respectively using the adaptive filtering and not using it. With the adopted adaptive filtering we obtained a Signal Noise Ratio improvement of about 10 dB. The figure clearly shows 8 ischemic episodes, corresponding to the 8 KL series peaks. Only 5 of them are reported in the database reference annotations, since 3 of these episodes (first, second, and seventh) are below the standard thresholds for marking ischemic ST-T episodes. Here these subthreshold episodes are unambiguously identified.

The second figure shows the first and the second KL components for the first lead of the e0105 record. In this case, each one of the seven peaks corresponds to an ischemic ST-T episode, marked in the database reference annotations.

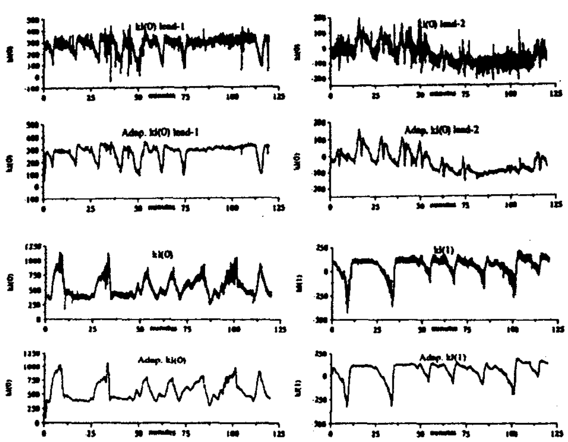

Figure 3. KL series with and without adaptive filtering.

5. Artificial neural network.

To detect ST ischemic episodes, we could apply a simple threshold criterion to the time series, because of their good quality. On the other hand that would not be able to avoid artefacts and to recognize weak ST episodes. It is necessary to yield also morphological information from the ST-T episodes in such a way to distinguish artefacts and to appreciate even subthresholds episodes. For that we need information from a sequence of beats instead of a single beat and a new decision criterion.

We decided to use the Artificial Neural Network approach, because it was applied in other ECG automatic analysis problems, obtaining very good results [6]. So, a three-layer feedforward neural network, trained with BackPropagation, was applied to the KL series for each record, to recognize the ST-T level changes.

Each input pattern consisted of 28 features, characterizing a 7 beat signal window, and each beat was described by the first 4 KL coefficients of its ST-T segment. 3 output units were introduced to indicate respectively ST depression, ST elevation, and artefacts, with a mutually exclusive code. Thus a normal ST-T segment was coded with a [0 0 0] target vector. The hidden layer, after several experiments, was chosen to have 10 units. All units of the network had the sigmoidal activation function.

The training set was built by using only 10 out of the 100 ST-T database records and the test was performed on the remaining 90 ones. From the 10 records used for the training set, a subset of representative artefacts, normal, and abnormal beats, almost equally distributed, was extracted, for a total of around 2,000 ST-T segments.

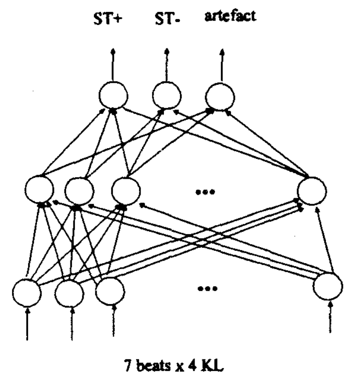

Figure 4. Neural network structure.

For each record, the first 60 ST-T segments were used to calculate the average level of its KL series, so that we could regard every ST episode as a change from the 0 level. For the training set, only records with a stable baseline level were chosen. In the test set, the average level, calculated at the beginning, was updated on every point by using a moving average algorithm. This operation was interrupted when either an ST episode or an artefact was detected and after that the new average KL level was calculated.

The input and output values were normalized to fall in the range [0,1]. During the learning process of the network we adopted two possible stopping criteria: either if the epoch number is greater than 2,000 or if the Root Mean Square error, calculated on the output layer, is less than a threshold value, heuristically fixed at 1,000.

To avoid too slow convergence of the learning process and at the same time too many oscillations of the RMS error function, the learning rate was adaptive, with 0.1 as initial value. The momentum term was fixed set to 0.01 for the entire learning process.

For final diagnosis, a threshold criterion was applied to the network outputs. During the training process, the network learnt very fast to give symmetric answers for ST depression and ST elevation outputs, so that the usual uncertainty criterion of refusing diagnosis with close outputs was not too helpful.

After the network processing, a duration criterion was introduced, to reject too short ST episodes.

In fact, physicians, usually, take care only of the ST episodes lasting at least 15 seconds, then a duration threshold of 15 seconds was adopted. Moreover two subsequent ST episodes were considered only one if the time distance between them was shorter than 5 seconds. The ST episode detection was performed on each ECG lead separately, to obtain a more accurate detection and a more reliable comparison with the annotated ST episodes of European database. In fact sometimes the ECG records show ST level changes only in one lead.

6. Results.

For the evaluation of the complete system performance, we defined the sensitivity as the percentage of correctly detected ST episodes among all ST episodes in the database and the Positive Predictive Accuracy (PPA) as the percentage of correctly detected ST episodes respect to all the detected ST episodes. An ST episode was regarded as correctly detected if its duration overlapped the duration of the corresponding annotated ST espisode at least for the 50%, otherwise it was considered as a false positive.

Table 1. System performance for different training sets.

	sensitivity	PPA
600 ST+ 600 ST- 0 artefacts	73%	66%
600 ST+ 600 ST- 400 artefacts	77%	82%
600 ST+ 600 ST- 600 artefacts	77%	82%
800 ST+ 800 ST- 800 artefacts	77%	86%

Several detection thresholds were tested on the network output layer with values around 0.5. The best one is resulted that one with value 0.7, even more to reject ambiguous artefacts and then to have good values for PPA. In the table 1, some results are reported, considering several training set compositions and the best value of detection threshold (0.7).

Of course, it is hard to evaluate the system performance about artefact detection, because they are not annotated in the European ST-T Database. We can only observe that when the number of artefacts in the training set increased, the PPA increased too. That means that the network got able to correctly recognize artefacts.

7. Conclusions.

We can observe that this combination of Karhunen-Loève transform for information representation and Artficial Neural Network for final classification gives good results, around 80% for both sensitivity and Positive Predictive Accuracy. These performances are better than those given by the commercial systems on the European database. Moreover these performance figures are very close to those of a trained cardiologist, as it is reported in literature[2]. The system sensitivity is quite high and it is interesting to note that several weak ST episodes not annotated in the database are quite well recognized by our system, which improves the system sensitivity. The network is able too to correctly detect artefacts, at least with an adequate training set. On the other hand it is impossible to describe in the training set every kind of artefacts, because their features are not uniform at all, for depending on too many factors. Neverthless we tryed to extend the training set even to new shapes of artefacts, but in that case the convergence of the learning process was not guarranteed.

Someones of these problems could be likely solved by introducing more information into the system. It is possible that lack of information is already in the ECG signal having only two leads. We should investigate possible improvements derived from adding further ECG leads to the analysis. It could be interesting also to investigate a new transform operator able to distinguish all the artefacts from any ST episode.

In any case, these results show how a good preprocessing technique, as the Karhunen-Loève transform, and a non-linear decision process, as neural networks, can extract very complicate rules even from a reduced training set, with only 10 records out of 100!

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