

Relative Estimation of the Karhunen-Loève Transform Basis Functions for Detection of Ventricular Ectopic Beats

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Abstract

Feasibility of the Karhunen-Loève transform (KLT) for detection of ventricular ectopic beats was studied. The KLT basis functions of normal QRS complexes were derived for a small-sized training set of heartbeats. The relevant KLT features were obtained by comparison between five selected heartbeats of the predominant rhythm and the remaining heartbeats in the tested electrocardiographic (ECG) recording. Statistical analysis of the KLT features for MIT-BIH arrhythmia database contributed to the definition of threshold criteria for discrimination between the predominant and the ventricular ectopic heartbeats. The achieved accuracy was about 97.7% for single-lead analysis and above 98% for joint two-lead processing. The method is attractive and suitable for implementation in an automatic analysis module because of the necessity for supervisor annotation of only five beats of the predominant rhythm in one ECG recording.

1. Introduction

Automatic heartbeat classification using the electrocardiogram (ECG) has been a field of intensive research during the last years. Recently a number of sophisticated ECG modeling methods, competing for higher accuracy, were published. Classical techniques use heuristic ECG descriptors, such as the QRS morphology [1,2]. However, the QRS pattern recognition techniques are considerably affected by noise due to unfavorable signal acquisition conditions. Another group of approaches, theoretically more robust to noise, are based on approximating the QRS complex using a small number of waveforms taken from a suitable dictionary. For example, the Matching Pursuits method has been recently introduced for linear expansions of the QRS waveforms involving non-orthogonal dictionaries based on Wavelet Packets [3,4]. Other noise-tolerant parametric models of the QRS complex use common dictionaries of orthogonal basis functions. Examples of such basis are the Hermite functions [5,6] and the Karhunen-Loève transform (KLT)

[7], both providing a low dimension feature space for heartbeat classification. The KLT has also been successfully applied for reconstruction of the ST-T shape in studies of the ventricular repolarization period [8,9]. The KLT was preferred because of its power to approximate a selected segment from the P-QRS-T pattern with both the lowest expected mean-squared error and enhanced noise immunity.

The present study investigates the ability of defined KLT features to improve the accuracy of the KLT method [7] for discrimination between ectopic beats and the beats of the predominant rhythm in one ECG recording.

2. Materials and methods

2.1. ECG database

We analysed 44 of the 48 ECG recordings of the Massachusetts Institute of Technology - Beth Israel Hospital (MIT-BIH) arrhythmia database. We excluded the 4 files with paced beats (102, 104, 107, 217). Each recording has a duration of 30 min and includes two leads – the modified limb lead II and one of the modified leads V1, V2, V4 or V5 [10]. The sampling frequency is 360 Hz and the resolution is 200 samples per mV. The heartbeats were recognized by the fiducial points in the database. We followed the American Heart Association (AHA) records equivalent annotation [10] to form two classes of heartbeats: (i) the class of the ventricular ectopic beats (V); (ii) the class of the normal beats (N), including all normal heartbeats (approximately 70% of the database) and some of the abnormal beats (left bundle branch block, right bundle branch block, aberrantly conducted beat, nodal premature beat, atrial premature beat, nodal or atrial premature beat, nodal escape beat, left or right bundle branch block, atrial ectopic beat and nodal ectopic beat). We further restricted the N class to contain only those heartbeats, which are representative for the predominant rhythm of the patient - normal beats, left bundle branch block and right bundle branch block beats. No selection based on the quality of the signal was performed. Thus the analysis was applied even in the presence of artifact or noise in the ECG.

2.2. Preprocessing

The preprocessing of the ECG signal was performed using online filters suitable for real-time operation of the V/N classifier. It involves: (i) a notch filter for elimination of power-line interference, implemented by moving averaging of samples in one period of the interference; (ii) a low-pass filter for suppression of tremor noise, realized by moving averaging of samples in 30 ms time-interval, thus having a first zero at about 35 Hz; (iii) a high-pass recursive filter for drift suppression with cut-off frequency of 2.2 Hz. The detailed description of the pre-processing filters can be found in [1].

The temporal representations of each beat's QRS complex was obtained as in [7], where the ECG signals (sampled at 360 Hz) were decimated by a factor of 3 and each QRS complex at each channel was represented by a 200-ms period starting roughly 60 ms before the fiducial point and ending 140 ms after the fiducial point. As a result, each QRS complex was represented by 24 samples at each data channel.

2.3. QRS pattern representation by the Karhunen-Loève transform

Let us denote by $\mathbf{X} = (\mathbf{x}_1, \dots, \mathbf{x}_n)$ the $24 \times n$ matrix having as columns the representations of a set of n QRS complexes. We aim to design a linear transform matrix $\mathbf{B} = (\mathbf{b}_1, \dots, \mathbf{b}_k)$ of dimensions $24 \times k$ such that the transformed QRS complexes $\mathbf{Y} = \mathbf{B}^T \mathbf{X}$ can be more easily clustered into classes N and V. The columns of our transform matrix $\mathbf{b}_1, \dots, \mathbf{b}_k$ are referred to as transform functions and the elements of the transformed data vectors \mathbf{Y} are often called signal coefficients in the transform domain. It would be desirable that $k \ll 24$ which means that we reduce the number of descriptors for each QRS complex and, therefore, we decrease the complexity of the classifier.

2.3.1. Derivation of KLT basis functions

As was originally proposed in [7], we use a subset of the KLT basis functions to design the linear transform matrix that will compress the useful class information of each QRS complex. The KLT basis for a finite number of QRS complexes is defined as the n eigenvectors of their sample covariance matrix [11]:

$$\mathbf{R}_X = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i \mathbf{x}_i^T$$

Let us denote by $\mathbf{v}_1, \dots, \mathbf{v}_k$ the k eigenvectors of \mathbf{R}_X corresponding to the k largest eigenvalues ($k < 24$). Then, we can define an incomplete KLT transform matrix by $\mathbf{B}_{KLT} = (\mathbf{v}_1, \dots, \mathbf{v}_k)$. Such transform matrix satisfies, for

a fixed number of columns of the transform matrix, the following optimality condition:

$$\mathbf{B}_{KLT} = \arg \min_{\mathbf{B}} \left\{ \sum_{i=1}^n (\mathbf{x}_i - \mathbf{B} \mathbf{B}^T \mathbf{x}_i)^T (\mathbf{x}_i - \mathbf{B} \mathbf{B}^T \mathbf{x}_i) \right\}.$$

That is \mathbf{B}_{KLT} attains the minimum mean squared reconstruction error (MMSE) for the observed QRS complexes. This means that the incomplete KLT transform effectively compresses the major QRS structures.

2.3.2. Training set for derivation of KLT basis functions

The KLT basis functions were derived to approximate the QRS complex pattern for the beats in class N. We composed a small-sized training set of heartbeats, which were chosen to outline the variety of N waveforms that appeared in each file. Therefore, the analyzed ECG recordings were represented in the learning set by five heartbeats of their predominant rhythms. Only 3 files were represented by 10 beats because two types of predominant beats were observed, i.e. 212 and 231 files contain normal and right bundle branch block beats, 207 file contain right and left bundle branch block beats. Thus the training set was formed by a total number of 235 beats – 185 normal beats, 20 left bundle branch block beats and 30 right bundle branch block beats. By manually selecting the prototypical QRS complexes in each recording we effectively discarded noisy or irrelevant beats in the computation of the QRS complexes auto-covariance matrix. This made unnecessary the use of auto-covariance estimation techniques robust to noise, as the used in [7].

2.3.3. Estimation of relative KLT features

The first 10 KLT basis functions were used to compute the relevant KLT coefficients for the training set of heartbeats and for the testing set of heartbeats. The testing set comprised all QRS complexes that were not used for training and belonged to the selected heartbeat classes.

The relative estimation of the QRS wave shapes of the training and the testing beats, i.e. the comparison between the relevant KLT coefficients, advanced the definition of the following features for every beat in the testing set:

- CSUM: We computed the average KLT coefficients, across all training heartbeats in the ECG recording. CSUM represents the mean value of the differences between the test heartbeat's KLT coefficients and the average KLT coefficients of the training set.
- CSUM_MIN: We computed the mean difference between the KLT coefficients of the test beat and the corresponding coefficients of each training beat.

CSUM_MIN is the minimum of those average differences.

- COINC: We compared the tested heartbeat with each of the training heartbeats belonging to the same ECG recording by calculation of the number of equal signed pairs of KLT significant coefficients (those with absolute value above 0.05). COINC stores the maximal normalized number of the equal signed pairs.

3. Results

The first 10 KLT basis functions that were calculated to approximate the QRS complex pattern of normal beats are presented in Figure 1.

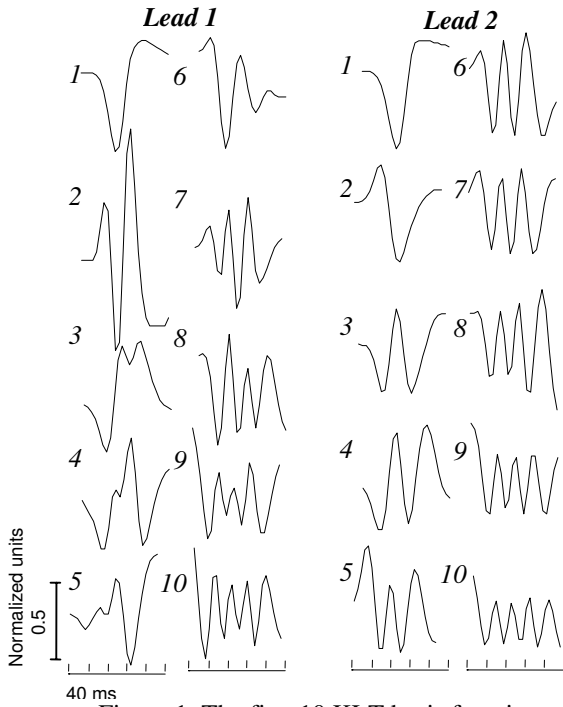


Figure 1. The first 10 KLT basis functions corresponding to Lead 1 and Lead 2.

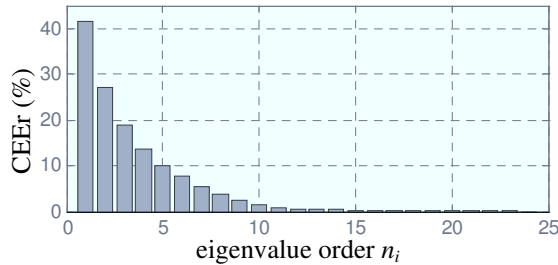


Figure 2. CEEr as a function of the eigenvalue order for the basis vectors estimated for Lead 1.

By analysis of the cumulative eigenvalue (e) error CEEr:

$$CEEr(n_i) = \left(1 - \left(\frac{\sum_{k=1}^{n_i} |e_k|}{\sum_{k=1}^n |e_k|}\right)\right) \cdot 100 (\%)$$

(Figure 2) we defined the number of basis functions for computation of the KLT features. An error of about 1 % could be provided by using the first 10 basis functions.

The KLT features defined above were computed for all beats ($N=92388$, $V=6901$). In Figure 3 we show the distributions of those features (CSUM, CSUM_MIN, COINC) for the two heartbeat classes. The presented distributions allowed the definition of the following thresholds for discrimination of the heartbeats belonging to class N:

$$(CSUM_MIN \leq 1.2) \text{ or } ((CSUM \leq 1.5) \text{ or } (COINC = 1))$$

All other beats are classified as V beats.

Applying the above defined criteria, we calculated the specificity (Sp) and the sensitivity (Se) representing the accuracy for the classification of N and V beats, respectively. The statistical indices are derived for single-lead analysis (Lead 1), as well as for joint analysis of the two leads (Lead 1+Lead2) (Table 1).

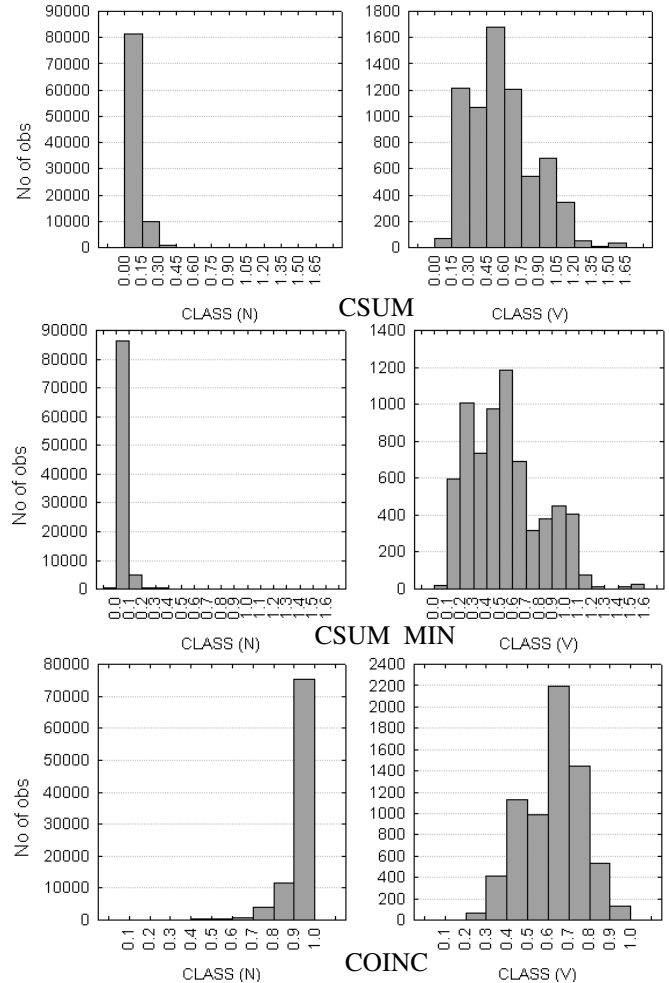


Figure 3. Histograms of the relative KLT features for the two heartbeat classes (N and V) for Lead 1.

Table 1. Specificity (Sp) and Sensitivity (Se) for different combinations of the relative KLT features - assessment for *Lead 1* and *Lead 1+Lead 2*.

KLT features	MIT-BIH leads			
	<i>Lead1</i>		<i>Lead1+Lead2</i>	
	Sp [%]	Se [%]	Sp [%]	Se [%]
CSUM_MIN	96.17	99.03	94.7	99.62
CSUM	88.3	98.97	88.36	99.45
COINC	81.27	98.96	91.19	99.26
CSUM_MIN+CSUM	97.15	98.45	96.53	99.42
CSUM_MIN+COINC	96.86	98.25	96.58	99.03
CSUM+COINC	95.23	98.09	97.14	98.9
CSUM_MIN+CSUM+COINC	97.63	97.7	97.73	98.88

4. Discussion and conclusion

The application of the KLT allowed us to reconstruct the major QRS components using a relatively small number of KLT basis functions (the first 10). By defining a small set of beats for each ECG recording and considering the observable differences between the shapes of the N and the V beats we were able to use the KLT coefficients to discriminate between the predominant and the ventricular ectopic beats within the same ECG recording. The statistical assessment of the derived relative KLT features (CSUM, CSUM_MIN, COINC) for MIT-BIH arrhythmia database showed considerably different distributions for the 2 heartbeat classes. This allowed the definition of simple threshold criteria for fast automatic heartbeat classification. The achieved sensitivity and specificity are comparable to the values reported by other authors [1-4,6,7], who published methods based on joint information for two ECG leads and large training sets. The advantages of the presented method are:

- Possibility of using only one ECG lead and only one feature CSUM_MIN, which searches for the best QRS shape similarity between the tested beat and one of the few training predominant beats in the ECG recording: CSUM_MIN attains Sp=96.2%, Se=99% for *Lead1*.

- Possibility to use only one ECG lead and to combine up to 3 KLT features in order to obtain Sp=97.2%, Se=97.7% (for *Lead 1*) – see bolded cells in Table 1.

The specific implementation of KLT single-lead analysis, which for example is applicable in emergency monitors, could be easily extended to multi-lead processing of the defined KLT features. The expected accuracy improvement was confirmed with *Lead1+Lead2* and the best results were obtained for: (i) 2 KLT features - Sp=96.5%, Se=99.4%, (ii) 3 KLT features - Sp=97.7%, Se=98.9% (bolded cells in Table 1).

The method is attractive and suitable for implementation in an automatic analysis module because of the necessity for supervisor annotation of only five beats of the predominant rhythm in one ECG recording.

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