Analysis of the Cardiac Repolarization Period Using the KL Transform: Applications on the ST-T Database *

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Abstract

The ST-T segment of the surface ECG reflects cardiac repolarization, and is quite sensitive to a number of pathological conditions. ST-T changes generally affect the entire waveshape, and are inadequately characterized by single features such as depression of the ST segment. Metrics which represent overall waveshape should provide more sensitive indicators of ST-T wave abnormalities. This study presents a Karhunen-Loeve Transform (KLT) technique for the analysis of the ST-T waveform. This technique recovers maximun information from a minimum number of parameters for a given set of waveforms. The training data yielded a KL basis set which concentrates 90% of the ST-T signal energy in the first four coefficients. The KL technique was used to analyze the ST-T complexes in the ESC ST-T database. KL coefficients were plotted as a function of time, and were effective in detection of transient ischemic episodes. Twenty percent of the records showed bursts of periodic ischemia suggesting local vascular instability.

1. Introduction

The ventricular repolarization (VR) process of the heart can be observed indirectly in the electrocardiogram during the ST-T complex. Variations in VR, observed as variations in ST-T morphology, reflect a variety of pathologies that account for a high incidence of sudden cardiac death (SCD) in developed countries. Disorders in VR may result in increased susceptibility to ventricular fibrillation (VF), which leads to SCD within minutes without intervention.

At present, there are no generally accepted non-invasive indices of the risk of SCD. Indices derived from isolated features of the ST-T complex are commonly used to describe VR, a practice that reflects the difficulty of deriving integrated measurements using visual analysis. Given the significance of the spatiotemporal evolution of VR throughout the entire ST-T complex, there is good reason to believe that differential measurements such as ST levels [1] and QT intervals fail to represent significant features of VR. These considerations led us to develop an analytic technique based on the Karhunen-Loève transform (KLT) and entire ST-T complex.

The KLT [2] is a signal-dependent linear transform that is optimal in the following sense: for any given number of parameters n, if the input is reconstructed from the first n terms of the series expansion of a linear transform, the lowest expected mean-squared error will be obtained if the transform is chosen to be the KLT. Then it concentrates the maximum signal information in the minimum number of parameters, and it defines the domain where the signal and noise are most separated. A KLT for a given type of signal must be derived from the statistics of examples of that signal. Thus, a significant limitation of the KLT is that it is necessary to collect a representative "training" set of the signals to be analyzed, in order to derive the KLT basis functions (eigenfunctions). The performance of the KLT depends on how well the training set has been constructed.

In this study, we have applied the KLT to the entire ST-T complex, in order to include as much information about VR as possible. We selected a large training set, including recordings from the MIT-BIH Arrhythmia Database CD-ROM [3], from the European ST-T Database [4], from a collection of ECG recordings of healthy subjects gathered at Boston's Beth Israel Hospital (BIH), and from a collection of SCD recordings assembled at BIH from several sources.

We apply these techniques to ECG records from the European ST-T Database, and we show how the first and second *kl* series may be used to monitor ST segment changes in these records. We illustrate this point with examples of periodic behavior of the ischemic process within these records.

2. The Karhunen-Loève transform

We represent each ST-T complex first by a *pattern vector*, $\mathbf{x}$, the components of which are the time-ordered samples of the ST-T complex (after baseline correction and normalization). The KLT is a rotational transformation of a pattern vector into a *feature vector*, the components of which are the coefficients of the KLT. As shown below, the first few components of the feature vector represent almost all of the signal energy, and the remaining components need not even be computed.

The derivation of the KLT basis functions begins by estimating the covariance matrix $\mathbf{C}$ of the pattern vectors of the training set [2],

$$\mathbf{C} = E\{(\mathbf{x} - \mathbf{m})(\mathbf{x} - \mathbf{m})^T\} \quad (1)$$

where $\mathbf{m}$ is the mean pattern vector over the entire training set. The covariance matrix reflects the distribution of the

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pattern vectors in the pattern space. The orthogonal eigenvectors of C are the basis functions of the KLT, and the eigenvalues, λ_k, represent the average dispersion of the projection of a pattern vector onto the corresponding basis function. After sorting the eigenvectors in order by their respective eigenvalues, such that $\lambda_k \geq \lambda_{k+1}$, for $k = 0, 1, ..., N-1$, the corresponding basis functions are arranged in order of representational strength. The basis function corresponding to the largest eigenvalue is that function best able to represent an arbitrary pattern vector from the training set; the next function is the (orthogonal) function best able to represent the residual error obtained from fitting the first function, etc. The value of N is equal to the number of components in the pattern vector, and depends on the length of the waveform and on the sampling frequency; in this case the length is 600 ms, and the sampling frequency is 250 Hz, so that $N = 150$.

In this study, the mean pattern vector $\mathbf{m}$ can be forced to be zero, if we assume that each ST-T complex in the training set can represent both itself and its inverted counterpart. This represents the possibility that any ST-T complex may appear inverted simply as an artifact of the choice of the lead polarity when recording the ECG. Thus, the covariance matrix may be expressed simply as

$$\mathbf{C} = E\{(\mathbf{x})(\mathbf{x})^T\} \qquad (2)$$

and the eigenvalues, rather than representing the average dispersion of the ST-T projection onto the associated basis function, instead represent the average energy of this projection.

2.1. The training set and basis functions

To obtain a representative training set of normal and abnormal ST-T waveforms we have selected a wide variety of ECG records, 105 in all (15 from the MIT-BIH Arrhythmia Database, 6 from the MIT-BIH ST Change Database, 13 from the MIT-BIH Supraventricular Arrhythmia Database, 10 recordings of healthy subjects from BIH, 33 from the European ST-T Database, 4 from the MIT-BIH Long-Term Database and 24 from SCD recordings collected at BIH). From each of these 105 recordings, a 15-minute excerpt was selected. Since the noise discrimination power of the KLT depends on the distribution of the pattern vectors as reflected in the covariance matrix, we tried to avoid including segments that were obviously corrupted by baseline wander or other noise.

From these 105 fifteen-minute records, we have selected the training set of ST-T complexes according to the following procedure. First, QRS complexes were detected and labeled using ARISTOTLE software [5]. We defined the ST-T complex as the portion of the signal within a window beginning 85 ms following a QRS mark, q_i, and ending 240 ms prior to the next QRS mark, q_{i+1}. If the RR interval, rr_i (defined as the interval between the QRS marks), is less than 720 ms, the end of the window is located at $q_i + \frac{2}{3}rr_i$ (i.e., 2/3 of the way from the initial QRS mark to the following one).

To avoid the effects of ectopic and other abnormal beats on the ST-T complex, we accepted only ST-T complexes associated with QRS complexes labeled as normal by ARISTOTLE [6], and further required that both the previous and following QRS complexes be also labeled as normal. For each beat, we estimated the isoelectric level as the average signal value during the 20 ms interval beginning 80 ms prior to the QRS mark. Beats for which the estimated isoelectric level differed by more than 0.2 mV from that of the previous or following beat were excluded from the training set. We then manually rejected a small number of ST-T complexes we judged subjectively to be particularly noisy. The remaining 97,663 ST-T complexes formed the training set. We also used cubic splines for baseline removal.

The pattern vectors were normalized by magnitude (i.e., scaled such that the signal energy was constant); in this way, each pattern vector is accorded equal importance when deriving the KLT basis functions. Since the durations of the ST-T complexes vary (the final part of the ST-T complex is not always available due to the appearance of the next P-wave and QRS complex), the estimation of certain elements of the covariance matrix is problematic. We address this issue by estimating each element of the covariance matrix using only those ST-T complexes for which the corresponding elements are available. This procedure avoids introducing artifacts of the window definition into the covariance matrix estimate; its consequence is that the final portions of the derived basis functions are derived from a smaller sample than the initial portions.

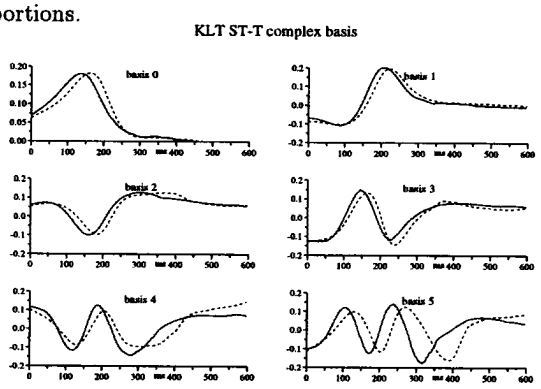

Figure 1: *KLT basis functions. The solid lines show functions derived without HR correction, while the dashed lines show functions derived with Bazett's correction.*

We have got that this representation permits about 90% of the signal energy to be represented by the first 4 *kl* coefficients. The first 6 KL basis functions are displayed in figure 1 (solid lines) together with those from Bazett's correction of the trayining set (dashed lines). It is apparent that the energy in the corrected set is concentrated at a later time than in the uncorrected set. Since most heart rates exceed 60 beats per minute, the correction applied to most ST-T complexes tends to stretch them (i.e., to move the concentration of energy toward the end of the window). The first basis function, and to a lesser extent the second one, represent the dominant low-frequency components of the ST-T complex 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

complex. These functions represent components present in abnormally prolonged ST-T complexes and in U waves where present within the window. The remaining higher-order basis vectors contain almost exclusively high-frequency content related to noise in the training set. By inspection of the basis vectors, we can predict that the first two KL coefficients, kl_0 and kl_1, should be a good tool for detecting ischemic ST-T changes, since they contain virtually all of the low-frequency energy.

2.2. KL representation of the ST-T waves

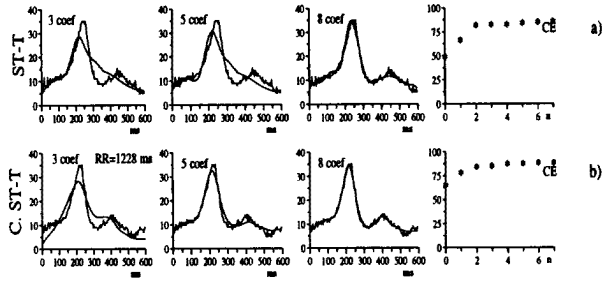

Figure 2: *Reconstruction of a ST-T complex with the KL transform.*

In figure 2 we present the reconstruction of a ST-T complex with 3, 5 and 8 KL coefficients, using uncorrected (a) and HR-corrected KL basis functions (b). The complex includes a prominent U wave. Since this feature is unusual, U waves were not common in the training set, and a faithful reconstruction requires more than the first few KL coefficients. The RR interval in this case is 1228 ms, implying only a small HR correction; we see, however (fig. 2b) how this small shift to the left results in a markedly better reconstruction with the low order coefficients. At the right, the cumulative signal energy ($CE(n) = 100 \sum_{i=0}^{n} kl_i^2 / \sum_{k=0}^{N} STT^2(k)$) is shown for each reconstruction.

3. Monitoring the kl series

In previous sections we have described how to derive a KLT representation of the ST-T complex. In clinical practice, the dynamic behavior over time of ST-T morphology is even more important than are the characteristics of an isolated complex. ST-T dynamics can be characterized by the study of KL coefficient time series, kl, using many of the techniques used in studies of HRV. We can assign to each beat mark (QRS fiducial point) the KL coefficients of its ST-T complex. In this way we will have as many (scalar) time series as there are KL coefficients needed to represent the ST-T complex. The direct way to monitor kl is to obtain it from the inner product of the KL basis with the pattern vectors of the ST-T complexes to be analyzed. These pattern vectors are obtained in the same manner as those in the training set (using cubic spline baseline removal).In this case, however, we do not normalize the energy of the ST-T complex pattern vectors, since we are interested in monitoring variations in energy as well as in morphology. The inner product is performed over the interval in which the ST-T complex is defined (not necessarily the entire window over which the basis function extends); this policy is equivalent to appending additional zero components to the pattern vector as needed to match its length to that of the basis function.

Direct estimation in this way, however, results in a noisy kl time series. Noise is introduced into the kl time series from a variety of sources, including noise in the ST-T complexes not removed by the KLT, residual error in the KL domain representation of the ST-T complexes, misestimation of the isoelectric level (because of noise in the PR interval, or QRS fiducial misestimation), residual baseline variations, and ectopic beats not rejected. Noise in the kl time series may be reduced using an adaptive filter that removes noise uncorrelated with the ST-T complex. This technique is useful for monitoring medium- to long-term variations in the ST-T complex, such as for detecting ischemic ST-T changes; when we are interested in beat-to-beat variations (alternans), direct kl estimation is necessary.

Adaptive estimation of quasi-periodic signals such as the ST-T complex permits reduction of noise uncorrelated with the signal, with attendant improvements in the ability to track subtle dynamic variations in these signals. It makes use of the recurring features of the signal and is based on the adaptive linear combiner [7].

3.1. Application to ischemic ECG signals

In this section we present the results of estimating and monitoring the kl values on several real ECG records. The parameters that we have selected for the LMS adaptive estimator are $\mu = 0.1$, with $n = 4$ KL base functions and $N = 150$ msamples.

Figure 3 illustrates kl time series, each two hours in length, for three ECG records from the European ST-T database. Fig. 3a compares the kl_0 series of record e0103 for each of the two recorded ECG signals, estimated as the inner product between the ST-T complex and the KL basis function. Fig. 3b shows the same series, obtained using the adaptive estimator with the parameters as given above, and showing a SNR improvement of about 10 dB compared with those of fig. 3a. Note the simultaneous appearance of ischemic ST-T changes in both signals, but with different characteristic patterns, repeated quasi-periodically. The figure clearly shows eight ischemic episodes, corresponding to the eight kl series peaks; only five of these are marked in the database reference annotations, since three of these episodes (1th, 2th, and 7th) are below the standard thresholds for marking ischemic ST-T episodes. The technique we present allows these subthreshold episodes to be identified unambiguously, and allows the long-term pattern of quasi-periodic ischemic change to be observed more clearly than would be possible otherwise.

Fig. 3c shows the kl_0 (left) and kl_1 (right) series of the first ECG signal (only) of record e0105, and fig. 3d shows their adaptively estimated counterparts. In this case, each of the seven peaks corresponds to an ischemic ST-T episode marked in the database reference annotations. By study of two or more KL coefficients in a single lead, we can easily monitor changes in ST-T morphology as well as changes in ST level.

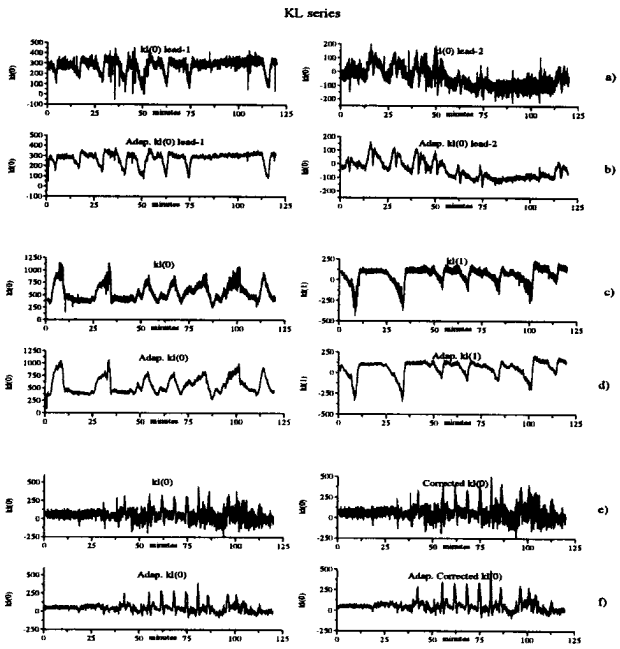

Figure 3: *kl plots for three records of the European ST-T Database. Panels (a) and (b) present kl_0 time series of record e0103 estimated directly from the inner product (a), and with the adaptive estimator (b); those on the left correspond to the first ECG signal, and those on the right to the second ECG signal. Panels (c) and (d) show the kl_0 time series for record e0105 on the left, and the kl_1 time series for the same record on the right. Panels (e) and (f) illustrate the uncorrected kl_0 time series for record e0113 on the left, and the corresponding HR-corrected kl_0 time series on the right.*

Finally, in fig. 3e are shown the uncorrected and HR-corrected kl_0 time series for the first ECG signal of record e0113, and in fig. 3f their adaptively estimated counterparts. As in the previous examples, the adaptive estimation of ST morphology tracks ischemic changes noted in the reference annotation files of the database. Note the slightly higher amplitude of the peaks in the HR-corrected series, showing that the first corrected *kl* basis function is better able to represent the ST-T complexes in this record than is the first uncorrected *kl* basis function. In fig. 3f, we note eight well-marked peaks that correspond to the seven marked in the database reference annotations, and one other (the second) that was not so marked, although it is quite clear from inspection of the *kl* series.

Analyzing the entire European ST-T Database (90 records) we found that roughly 20% of the records present these quasi-periodic ischemic ST-T changes, and that in another 20% more than one ischemic ST-T episode exhibit similar pattern in their associated *kl* time series.

4. Conclusions

In this work we have presented a KLT technique for studying the repolarization period of the heart throughout the ST-T complex of the ECG signal. We have developed a KLT training set of ST-T complexes, containing a broad range of morphologies, to obtain the KL basis vectors. We have shown that this representation permits about 90% of the signal energy to be represented by the first 4 *kl* coefficients. The KLT has been used to detect ST-T shape variations, with results demonstrating its suitability for detecting ST variations related to ischemic events. We have used an adaptive filter, for improving the signal-to-noise ratio of a time series of KL coefficients delivering an improvement of about 10 dB for a practical choice of parameters for monitoring ischemic ST-T changes.

In demonstrating the application of these techniques to analysis of the European ST-T Database, we have shown that about 20% of the records present a quasi-periodic pattern of ischemic ST-T activity, and another 20% exhibit repetitive but not clearly periodic patterns of ischemic ST-T changes. These observations are drawn from analysis of the entire ST-T complex; it would be difficult if not impossible to reach similar conclusions with confidence using classical differential measurements of ventricular repolarization such as measurements of ST level.

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