THE KL TRANSFORM AS A TOOL TO ANALYZE THE ST SEGMENT: COMPARISON WITH QT INTERVAL

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by

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Abstract

The spatial and temporal course of ventricular repolarization is quite sensitive to the biochemical and biophysiological environment of the myocardial cells, and is therefore often an early marker of heart disease, particularly of ischemia. The detailed morphology of the surface ECG contains considerable information about the repolarization process. The ST-segment changes with ischemia, injury, and drugs. The QT interval is affected by drugs, heart rate, and autonomic tone, and in some situations may identify individuals at high risk for arrythmias and sudden death. Variability in the shape, including duration, of the ST-T waves reflects autonomic nervous system activity, and may identify high-risk patients.

Automated methods for quantitatively characterizing ST-T complexes are of particular importance in studying long-term ECG records. We comparatively analyze two computer-based measurement procedures for characterizing the repolarization period: KL transform representation of the ST-T shape and measurement of beat-to-beat durations of repolarization (QT intervals).

We present the results of our work on KL transform representation and time-domain QT measurement algorithms for studying the repolarization period of the ECG on the European ST-T database. We found that about 20% of the records present a quasi-periodic KL pattern of ischemic ST-T activity, and another 20% exhibit repetitive but not clearly periodic patterns of ischemic ST-T changes. From these ischemic records 50% showed QT variations in at least one lead associated with the ischemic episodes.

1 Introduction

Electrocardiographic (ECG) information is derived from analysis of both the depolarization (QRS complex) and repolarization (ST-T waveform) phase of the cardiac electrical cycle through the information indirectly reflected on the surface ECG signal. Considerable interest has been directed at ventricular repolarization (VR) in recent years because subtle ST-T changes may be a marker of electrical instability that result in increased susceptibility to ventricular fibrillation (VF), which leads to sudden cardiac death (SCD), with a very high incidence in developed countries, within minutes without intervention. Repolarization may be perturbed by multiple factors including ischemia, structural heart disease, metabolic factors (e.g. electrolyte desrangements, drugs) and neuroautonomic factors.

At present, there are no generally accepted non-invasive indices of the risk of SCD, although such indices would have very substantial implications for both public health policy and medical practice, and many studies have sought to develop such indices. Among the most promising candidates are measurements of heart rate variability (HRV)[1, 2], ventricular late potentials[3, 4], repolarization duration (QT) interval[5, 6] measured with averaged measurements of QT interval (and related indexes of overall repolarization duration), QT variability[7, 8], assessment of heterogeneity of

repolarization (Q-T interval) in different leads, and repolarization alternans [9, 10] (a possible precursor of ventricular fibrillation). Except for the first two, all of these indices are derived from the ST-T complex of the ECG, which has long been known as a highly sensitive (though arguably less predictive) marker (ST level) of myocardial ischemia[11, 12].

Most of this indexes are derived from isolated features of the ST-T complex to describe VR, a practice that reflects the difficulty of deriving integrated measurements using visual analysis. However the ST-T waveform represents a complex spatial and temporal summation of electrical potentials from innumerable ventricular cells. Therefore, if physiologically and clinically relevant information is contained within the ST-T complex, this information may not necessarily be concentrated within any individual differential feature or subinterval such as ST levels and QT intervals, but may be represented by the entire ST-T waveform. The proliferation of additional "heuristic" measurements that describe the ST-T complex shape clearly demonstrates the need to consider more than the traditional measurements in order to characterize subtle changes in VR. Furthermore, noise and other sources of measurement error (such as fiducial or baseline misestimation) have far more deleterious effects on measurements of isolated features and simple differential measurements than on integrated measurements. These considerations, together with the increasing evidences for the importance of repolarization alterations as a marker of electrical instability and SCD, led us to develop an analytic technique based on the entire ST-T complex using the Karhunen-Loève transform (KLT) [13], and compare it with with classical measures on the ST-T complex as QT interval measured automatically with the method present in [14].

The KLT [15] is a signal-dependent linear transform that is optimal in the following sense: for any given number of transform 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. We selected a large training set (105 records, 15-minute excerpt), including recordings from the MIT-BIH Arrhythmia Database CD-ROM [16], from the European ST-T Database [17], 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.

The QT measurement problem is an apparently easy manual problem, with many complications

when performing automatic measures. Some methods are proposed in the literature to implement QT measurement. They try to solve the problem of detecting QRS wave onset and T wave end. The most difficult problem is to define the T wave end, because of its low frequency components. Some criteria for T wave end definition [18, 19] are based on deflection with reference to the baseline, while others make use of first derivative and some threshold [20, 21]. We use in this study one algorithm based on first derivative and morphology of each T wave [14] that has shown a error deviation comparative with that observed between different clinical experts.

We apply these techniques (KL and QT analysis) to ECG records from the European ST-T Database. 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. The QT analysis shows that this interval present noticeable variations at ischemic episodes in at least 50% of the ischemic records.

2 Methods

2.1 The Karhunen-Loève transform applied to the ST-T complex

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 [15],

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

where $\mathbf{m}$ is the mean pattern vector over the entire training set. The covariance matrix reflects the distribution of the pattern vectors in the pattern space. The orthogonal eigenvectors of $\mathbf{C}$ 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 pattern vector components, 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

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

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.

2.1.1 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. For details on the training set construction see [13].

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 training 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

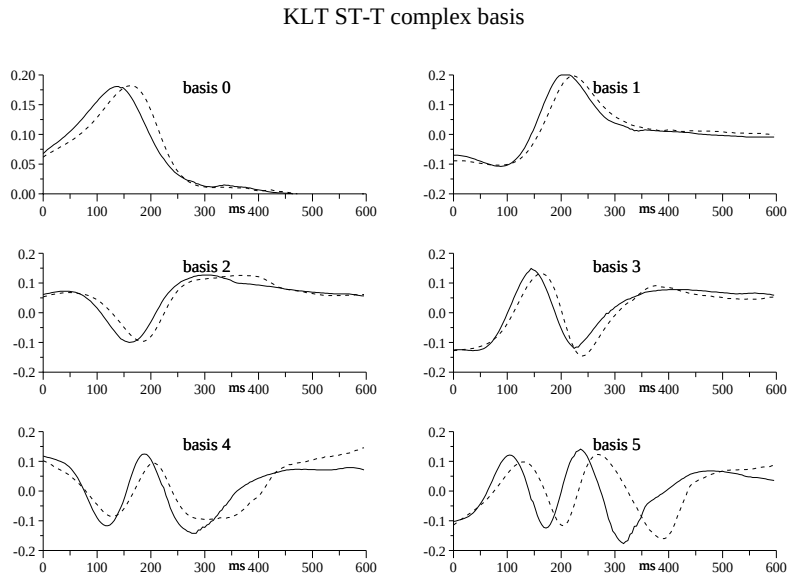

Figure 1: *KLT basis functions. The solid lines show functions derived without HR correction, while the dashed lines show functions derived with Bazett's correction.*

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.

2.1.2 KL representation of the ST-T waves

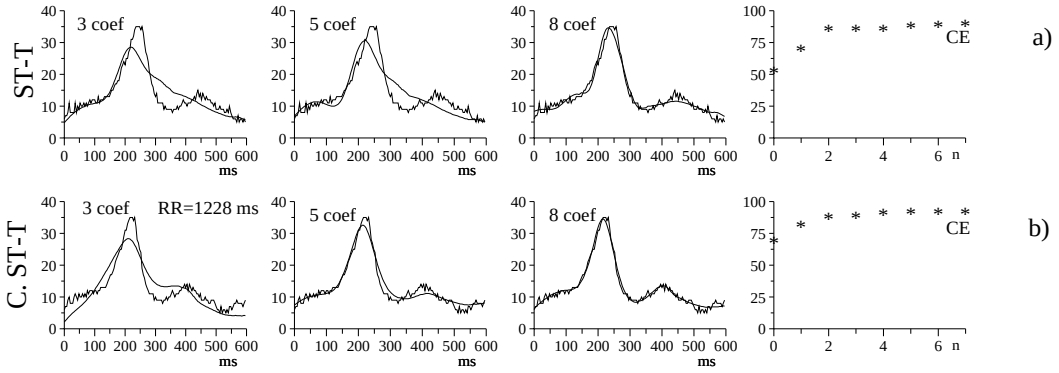

Figure 2: *Reconstruction of a ST-T complex with the KL transform.*

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.

2.2 QT measurement algorithm

The automatic procedure used to determine the significant points, Q onset and T end, is based on that presented in [14] that used criteria on the differentiated signal. The algorithm consist on: preprocessing, QRS detection, fibrillation process rejection, waves location and wave onset and end determination.

2.2.1 Preprocessing:

The first step consists of a filtering process for noise reduction and a non linear transformation to improve QRS detection [22]. The linear filtering uses a second order band-pass Lynn filter (0.8-18 Hz) to attenuate baseline drift and high frequency contamination. Once the band-pass filtered signal (ECGPB) is reached a low-pass differentiator is applied to get the information about changes in the signal slope. This differentiated signal is called ECGDER. The non linear transformation we use is the one described in [22].

2.2.2 QRS detection:

The QRS detector used in this work is the one proposed by Pan and Tompkins [22] considering information of the signal slope.

2.2.3 Fibrillation process rejection:

When a fibrillation process appears there is no sense in measuring P, QRS and T onsets and ends. The fibrillation process is detected by using the procedure presented in [23].

2.2.4 Waves location:

The QRS positions ($QRS(i)$) given by the detector may be Q, R or S wave peaks. From the $QRS(i)$ position in the ECGDER (zero-crossing in this signal) we search for the nearest peak positions before (p_b) and after (p_a). According to the polarity and relative value of these peaks we decide if

$QRS(i)$ in the ECG belong to Q, R or S wave position. The adjacent wave positions are detected as the nearest zero-crossing points to $QRS(i)$ in ECGDER. To admit these adjacent detected points as wave positions, the time distance between waves must be in the range of physiologically significant intervals, and the maximum slope associated with these waves must be bigger than a threshold of the maximum slope associated with the QRS complex. The threshold value is experimentally adjusted and is different for Q, R, S or R' waves, ranging from 3 to 10% of the maximum QRS slope value. With this procedure we have located the eventual Q, R, S and R' wave positions.

Next, we search for P and T wave positions. These waves have lower frequency components than the QRS complex. Then, we again apply a low-pass filter (cutoff frequency 12 Hz) to ECGDER to remove remaining noise. In this filtered signal (DERFI) we define a window of 155 ms starting 225 ms before the R position. This window is shortened when previous T or next Q waves are in it. In this window we search for the maximum and minimum value. If these values are bigger than 2% the maximum slope value of the QRS complex we consider presence of P wave, otherwise we consider P wave absence. P wave position is considered in the zero-crossing between the maximum and the minimum values in the window.

To detect T wave we define a search window in DERFI that is a function of the heart rate [21]. In this window we again search for the maximum and minimum values. According to their relative position and value we consider different shapes of T wave: regular, inverted, bi-phasic (+-) or bi-phasic (-+) [24]. T wave position is considered in the zero-crossing adjacent to the maximum or minimum value.

2.2.5 Waves onset and end determination:

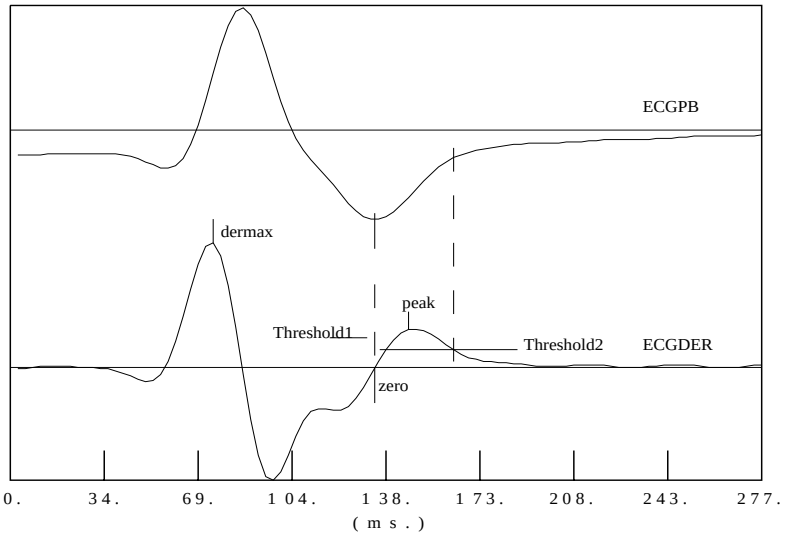

Figure 3: *Determination of QRS end by the threshold method.*

Once we have the wave locations (zero-crossing point (*zero*) in the differentiated signal ECGDER or DERFI), we proceed to determine the onset and end of each wave. The method used was presented in [21]. Figure 3 shows this procedure for QRS end determination. From the *zero* point we search for the adjacent peak (*pk*) on the right (for end) or on the left (for onset). This point is the highest slope point in the wave. With the value of ECGDER at time instant *pk* (ECGDER(*pk*)) we define a threshold (TH) as TH=ECGDER(pk)/k. Then, we determine the end (onset) point of the wave as the forward (backward) threshold crossing point from *zero* in the ECGDER signal. The value of k is a constant that is experimentally adjusted [14]. Figure 4 shows this procedure results on a single-lead ECG record from the MIT-BIH database.

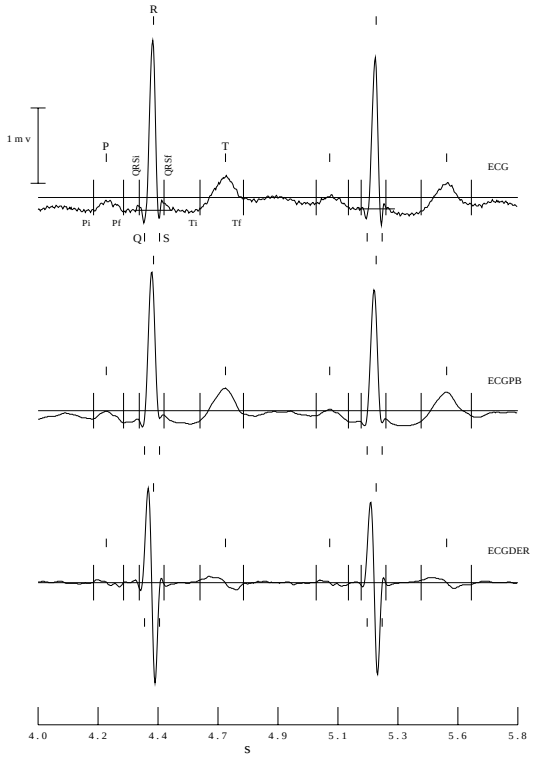

Figure 4: *Detection of characteristic points in two beats belonging to the 103 record (lead MLII) of the MIT-BIH ECG database. Short lines denote the wave positions (P, Q, R, S and T) and long lines the wave limits: P onset (Pb), P end (Pe) and so on. a) is the original ECG, b) the ECGPB signal and c) the ECGDER signal.*

3 Monitoring the kl series

In sections 2.1 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. 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 (see [13]).

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. We monitored the kl series making use of the adaptive filter presented in [13].

3.1 Application to real signals with ischemic episodes

In this section we present the results of estimating and monitoring the kl values on several real ECG records. Figure 5 illustrates kl time series, each two hours in length, for three ECG records from the European ST-T database. Fig. 5a compares the kl_0 series of record e0103 for each of the two recorded ECG leads, estimated as the inner product between the ST-T complex and the first (uncorrected) KL basis function. Fig. 5b shows the same series, obtained using the adaptive estimate, and showing a $\triangle SNR$ of about 10 dB compared with those of fig. 5a. Note the simultaneous appearance of ischemic ST-T changes in both leads repeated quasi-periodically. Note also the similarity of the temporal pattern of sequential ischemic episodes. 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 sub-threshold 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. Since the time series are initialized to zero, the time required for adaptation (at the left edge of each plot)

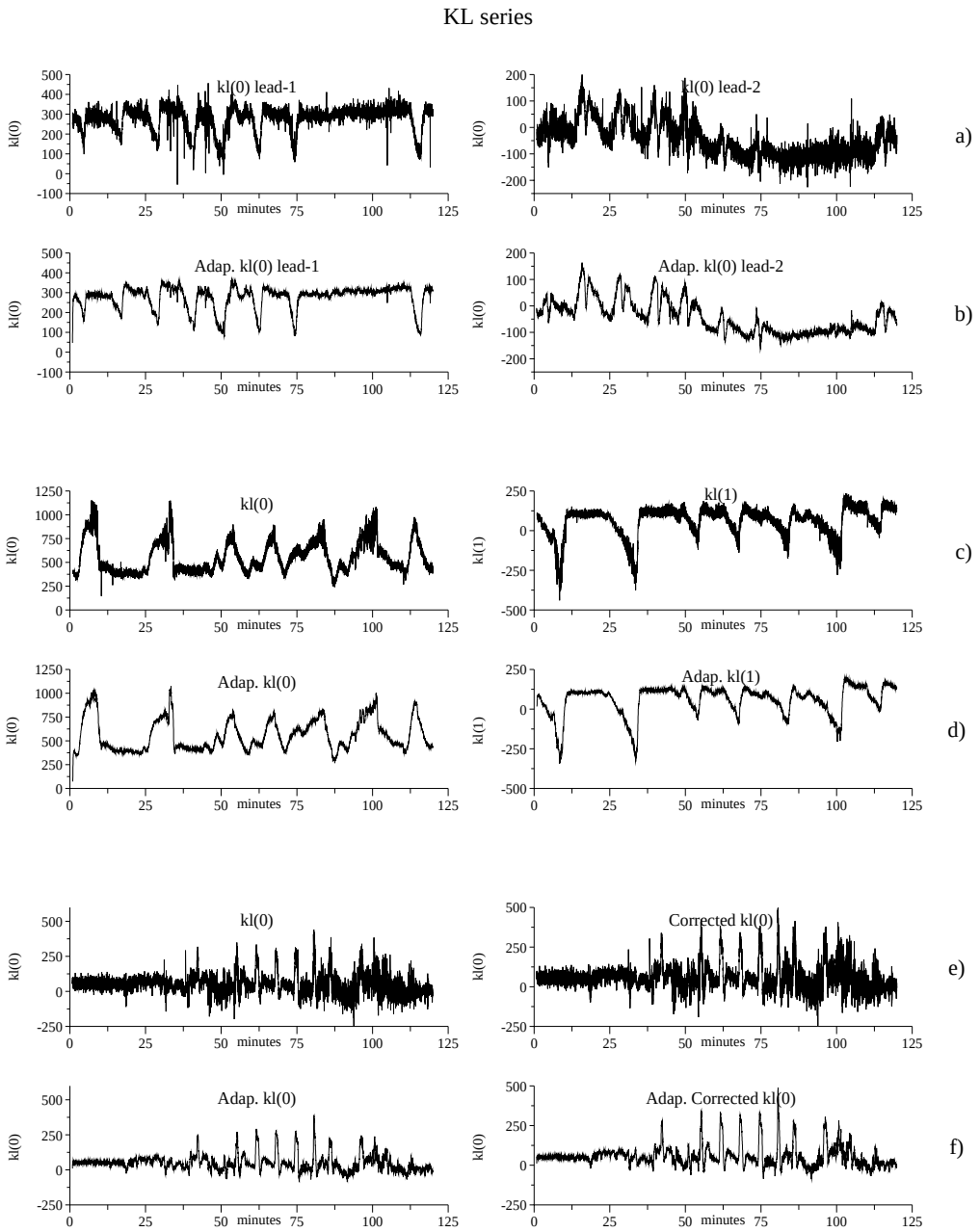

Figure 5: *kl plots for three records of the European ST-T Database. Panels (a) and (b) present kl_0 time series of record e0103 estimated directly from the inner product (a), and with the adaptive estimate (b); those on the left correspond to the first ECG signal, and those on the right to the second 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.*

can be seen to be negligible in comparison with the evolution of the ischemic variations.

Fig. 5c shows the kl_0 (left) and kl_1 (right) series of the first ECG signal (only) of record e0105, and fig. 5d 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. Note how the ST segment elevation that correspond to the ischemia at the e0105 record, results in increased kl_0 values and decreased (negative) kl_1 values, as pointed out in section 2.1.1 .

Finally, in fig. 5e are shown the uncorrected and HR-corrected kl_0 time series for the first ECG signal of record e0113, and in fig. 5f 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. 5f, 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 demonstrated the quasi-periodic salvos of ischemic ST-T changes shown in figure 5. In most records containing multiple ischemia episodes, we noted similarity in the temporal structure of their kl time series, suggesting a similar pathophysiologic mechanism.

4 Monitoring the QT series

In section 2.2 we have described how to derive the QT interval value of one beat. As with kl series, in clinical practice, the dynamic behavior over time is even more important than are the QT of an isolated complex. We can construct the QT series assigning to each beat mark (QRS fiducial point) the QT value. This series is affected by noise due to possible wrong estimations of particular QT values. Noise in the qt time series may be reduced using median filters [25] that select from a set of consecutive qt values the one whose value is in the meddle of the others. This technique is useful for monitoring medium- to long-term variations in the QT complex, when we are interested in beat-to-beat QT variations, this filter will underestimate this variations. However, for long-term variations this filters attenuates the error variance of the QT measure. In figure 6 is displayed the qt series for record e0103 of the ST-T database a) the original qt serie, b) after rejecting maximum and minimum QT values in each five consecutive beats set, c) Applying a median filter to the

five consecutive beats set (take the meddle value). d) as in b) but averaging the remaining three values, b) as in d) but taking seven consecutive beats set. Note how the variance of the qt series is reduced as de post-filtering is more severe (a) to d)) being more appropiated for long term variations, whereas for detecting beat-to-beat variations the original signal should be displayed (a)).

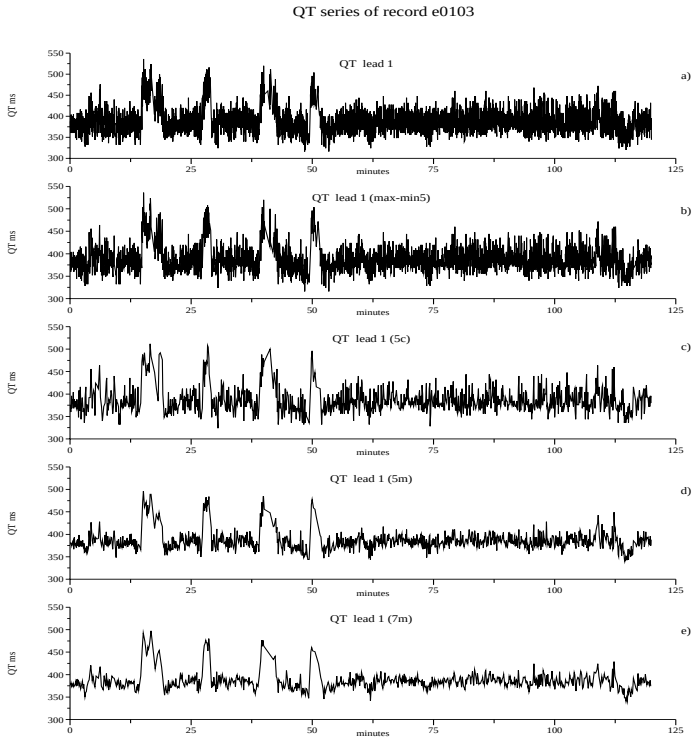

Figure 6: qt series from lead 1 of record e0103: a) original qt series, b) qt series rejecting maximum and minimum qt value in each five consecutive qt values set, c) qt series after applying a median filter (select the middle qt value) to each five consecutive qt value sets. d) qt series after rejecting maximum and minimum value in each five consecutive qt value sets and taking only the average value of the remaining three. e) same as d) but using seven values sets

5 kl series compared to qt series

Comparing the kl time series with the qt time series (averaging the value after rejecting the maximum and minimum value at the five beat sets), we have that, for example, in record e0103 (figure 7) the ischemic episodes are not clearly reflected at the QT series of lead 1 whereas at lead two the QT increases in the four first ischemic episodes and do not varies in the later three episodes. These variations are clearly ischemic related rather than heart rate related, as usually are the QT variations, as is noted at figure 7d where the qt series are heart rate corrected by the

Bazett's formula and still the qt variations remains after correction.

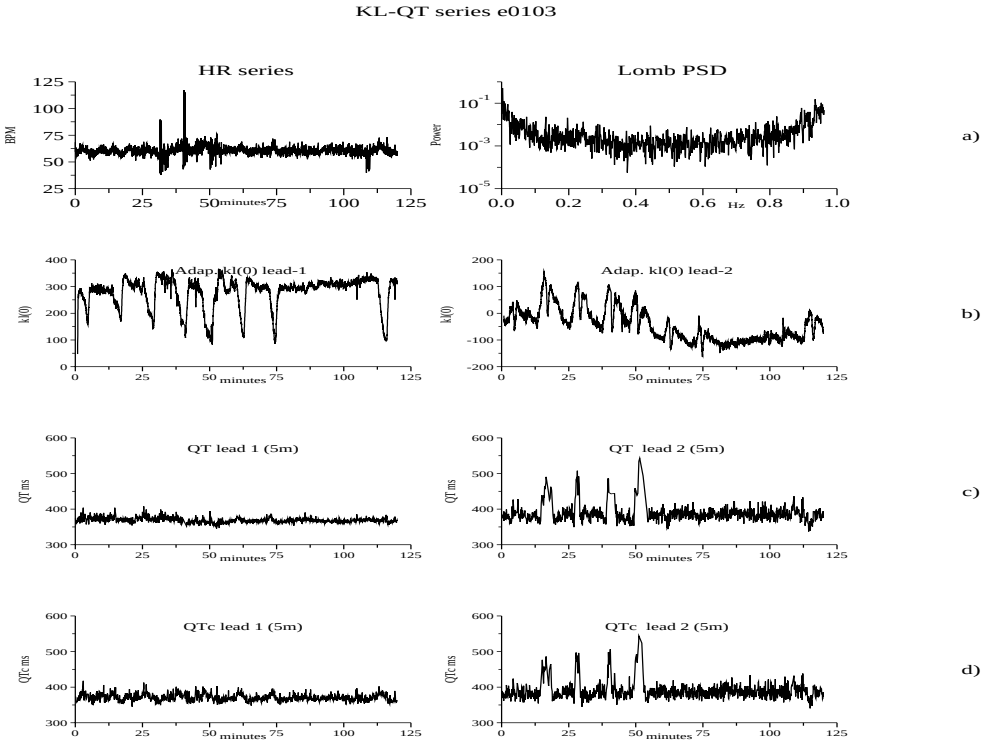

Figure 7: *kl and qt plots for record e0103 of the European ST-T Database. Panel (a) present the heart rate (left) and its power spectrum density (right), (b) present kl_0 time series estimated with the adaptive filter for lead 1 (left) and lead 2 (right), (c) present the qt series for both leads estimate as the mean after rejecting the maximum and minimum values in five beats sets. (d) show the Bazett's corrected qt series.*

In figure 8 we see that the ischemic process comes hight with HR variations. The qt variations related to ischemia again are maintained after Bazett's correction enphasaicing the ischemia related changes. The Bazett's formula is not a general dependence of qt with heart rate but in some cases allows to modelate the overall dependence. In figure 8d (right part) we see how the Bazett's correction rather than atenuate the qt value dependence with heart rate it is realced. This effect is due to the estability of the qt value in this patient and then agree with the hipothesis that the Bazett's correction is not a general acceptable correction.

Analyzing the entire European ST-T Database (90 records) we found that roughly 50% of ischemic records showed QT variations in at least one lead associated with the ischemic episodes.

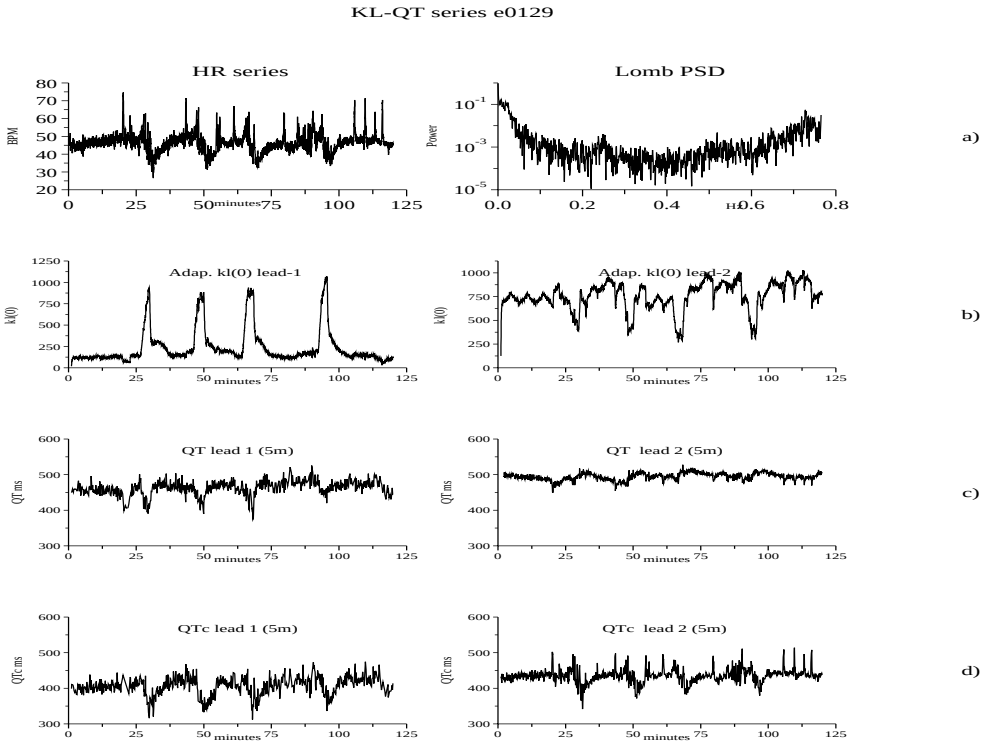

Figure 8: *kl and qt plots for record e0129 of the European ST-T Database. Panel (a) present the heart rate (left) and its power spectrum density (right), (b) present* kl_0 *time series estimated with the adaptive filter for lead 1 (left) and lead 2 (right), (c) present the qt series for both leads estimate as the mean after rejecting the maximum and minimum values in five beats sets. (d) show the Bazett's corrected qt series.*

6 Conclusions

In this work we have presented a comparative study of kl and qt series for studing the repolarization period of the heart throughout the ST-T complex of the ECG signal. The KLT has been used to detect ST-T shape variations, with results demonstrating its suitability for detecting ST variations related to ischemic events. An automatic procedure for QT measurement have been used to measure QT interval values and compare the qt series with the kl series on the same records.

In demonstrating the application of these techniques to analyze 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. Roughly 50% of these ischemic records showed QT variations in at least one lead associated with the ischemic episodes. These variations are scattered between shortening and prolongation, not been aevident any sistematics shortening as spected by the fact that the action potentials shorten during ischemia.

This technique can be used for long-term monitoring with a great potential for detection of transient ST-T changes, time occurrence location, measurement of ischemic episode durations, posterior localized review by the clynician, and other information extraction. Further studies will be necessary to show if this kl series give additional information to prevent sudden cardiac death episodes.

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