

FEATURE-BASED SEGMENTATION OF ECG SIGNALS

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ABSTRACT

Automatic segmentation of ECG signals is important in both clinical and research settings. Past algorithms have relied on incorporation of detailed heuristics. In this paper we propose a segmentation technique based on the best local trigonometric basis. We show by means of real data examples that the entropy criterion which achieves the most parsimonious representation of a signal results in an overly-fine segmentation of the ECG signal, and thus establish the need for a more comprehensive criterion. We introduce a novel best basis search criterion which is based on a linear combination of the entropy measure and a local measure of smoothness and curvature. We tested the algorithm on the MIT-BIH arrhythmia database.

1. INTRODUCTION

Automatic segmentation of an electrocardiogram (ECG) using a minimum of heuristic *a priori* information is an important problem in many clinical and research application areas. The various segments of an ECG have different physiological meaning, and the presence, timing, and duration of each of these segments have diagnostic and biophysical importance. The problem is made considerably more difficult because the shape of an ECG is quite variable both within and across patients. This intra-subject variability depends on a variety of factors such as the location of the electrode and the position of subject's body, in addition to perturbations such as measurement noise, muscle artifacts, and poor electrode contact. Variability is considerable even across healthy subjects; abnormalities such as insufficiency of oxygen supply to the cardiac tissue, (known as *ischemia*), usually caused by obstruction of coronary arteries, or premature initiation of heartbeats from non-standard locations on the heart (*e.g.* premature ventricular beats or other rhythm disorders) cause even greater potential for variability. Thus heavy reliance on heuristics in segmentation algorithms is problematic, as is the tuning of algorithms to any particular database. And yet one can usually segment these waveforms easily by eye. Thus the challenge is to develop automatic segmentation tools that are robust to inherent variability in the signal while relying on heuristics as minimally as possible. The approach we describe

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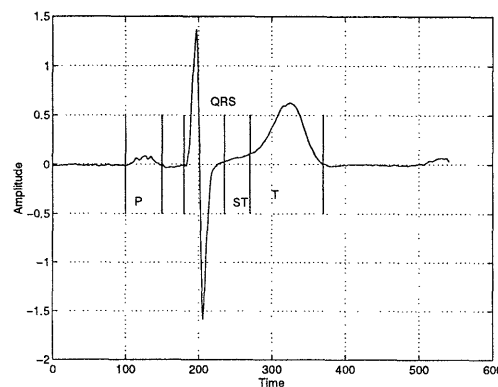


Figure 1: Typical annotated ECG.

below attempts to accomplish this by maximizing the algorithmic incorporation of the type of features which are typically of visual significance to a human observer.

Electrocardiograms are traditionally divided into four main electrical events, each reflecting the electrical activity associated with a particular phase of the cardiac cycle. These four events are named the P wave, the QRS complex, the ST segment, and the T wave, and are illustrated for a "typical" ECG by the annotations on the waveform in Figure 1. Each segment represents a specific physiological phase of the cardiac cycle. Because of the close tie between the segments of the ECG signal and the underlying physiological states, there has been considerable interest in the development of signal processing techniques to automatically perform this segmentation. In particular, automatic segmentation is important in applications such as patient monitoring, where the timing and duration of the segments in these recorded data can be used for a number of purposes. These range from simple detection of the presence/absence of a heartbeat to their use as the first step in algorithms to calculate an instantaneous or average heart rate or classify and detect ventricular or other abnormal beats. Initiation of an alarm signal or control over a pacemaker may also be governed by the output of such algorithms.

1.1. Segmentation by Best Basis Selection

Most previous approaches to this problem have combined simple signal processing techniques such as discrete differentiation and bandpass filtering with a large body of heuris-

tic rules, such as minimum and maximum lengths for each segment, complicated adaptive threshold criteria, frequency range criteria, signal templates, *etc.* (see, for example, among many others, [1, 2]). Other more recent approaches [3, 7, 4, 8, 9] have similarly relied on specific and overly restrictive rules. Reliance on heuristics causes sensitivity to the particular data-base from which they were developed and does not maximize use of the intrinsic information in the signal itself.

It is, however, often not difficult for an initiated operator to visually segment ECG signals with fewer heuristics than used by current algorithms. This indicates that there is inherent information in the signal itself which has not been exploited to date. In this work, we first cast the segmentation problem into one of searching for an adapted orthonormal basis, and then develop a deterministic criterion which mathematically incorporates as best as possible the information thought to have been of visual value. The notion of *Best Basis* (BB) has successfully been applied for wavelet packet bases (best spectral segmentation) as well as for Local Trigonometric Bases (LCB) (best temporal segmentation) [6].

It has been experimentally shown that parsimonious representation criteria can indeed achieve an acceptable delineation/segmentation for a number of signal classes. It is, however, not a universal criterion, in the sense that a *desired* segmentation may be expected to reflect features dictated by the morphology of a signal rather than by its parsimonious representation. It is thus imperative to construct criteria which should, in addition to parsimony, reflect the morphological structures of interest.

In the next section, we review some background material relevant to this paper. In Section 3, we describe the ECG segmentation algorithm which we substantiate with examples in Section 4. Section 5 gives some concluding remarks.

2. BACKGROUND

The choice of a wavelet for a given problem is as important as the analysis itself. It can be seen from Fig. 1 that the three "active" intervals, P, QRS, and T, have cosine-like or raised-cosine-like shapes although with quite different "periods" (or different frequencies), while the ST segment is marked by its DC or almost linear characteristic. The LCB thus provides a natural analysis framework which in turn results in an adapted segmentation.

Let our observed ECG signal be denoted by $x(t)$, $t = 1, \dots, K$ and in $\ell^2(\mathcal{Z})$. A LCB basis is constructed using a Malvar's wavelet or an oscillating waveform such as a sinusoid (or a cosinusoid) and a windowing function $g(t)$, which serves to ensure the compact support of the function as well as to preserve the orthogonality and complementarity properties between two successive segments. These functions satisfy the same hierarchical properties as wavelet packets and can be generated in a systematic way starting with a basis mother function:

$$w_{j,k}(t) = \frac{\sqrt{2}}{|I_j|} g_j(t) \cos \left[\pi(k + 1/2) \frac{t - t_j}{|I_j|} \right],$$

with $I_j = [c_j, c_{j+1})$ and $t_j = \frac{c_j + c_{j+1}}{2}$. The parameter k

controls the frequency of oscillation and $I_{(\cdot)}$ the extent and position of the support. The determination of $\{I_{(\cdot)}\}$ is the central issue of the *optimal* segmentation problem when using a LCB.

The determination of the "best representation" of $x(t)$ in a LCB generally relies on the minimization of a convex/concave criterion¹ which is a function of its coefficients $\{\mathcal{W}_{j,k}\}$, $j \in \mathcal{Z}$, $0 \leq k \leq (|I_j| - 1)$ in a set/dictionary of bases and which we denote here as $\phi_s(\{\mathcal{W}_{j,k}\})$. To maintain efficiency of the search for the BB, the dictionary \mathcal{D} of possible bases is structured according to a binary tree. Each node of the tree then corresponds to a given orthonormal basis \mathcal{B}_j of a vector subspace of $\ell^2(\{1, \dots, K\})$. An orthonormal basis of $\ell^2(\{1, \dots, K\})$ is then

$$\mathcal{B}_{\mathcal{P}} = \cup_{\{j\}/I_j \in \mathcal{P}} \mathcal{B}_j,$$

where \mathcal{P} is a partition of the total support into intervals I_j . By using the property

$$\text{Span}\{\tilde{\mathcal{B}}_j\} = \text{Span}\{\mathcal{B}_j\} \dot{\oplus} \text{Span}\{\mathcal{B}_{j+1}\}, \quad (1)$$

where $\tilde{\mathcal{B}}_j$ represents the basis with a merged support $I_j + I_{j+1}$, a fast bottom-up tree search algorithm to optimize the partition \mathcal{P} was developed in [11]. As first described by Coifman, Meyer [5] the search is carried out by pruning the tree via an efficient comparison of a "children" segmentation to a "parent" segmentation² in light of the associated costs.

2.1. Optimization Criteria

The merits of the various representations are based on comparing associated costs resulting from the basis coefficients. The underlying evaluation can be cast into a majorization theoretic framework, where the distributions of components of two vectors \mathbf{y}_1 and $\mathbf{y}_2 \in \mathcal{R}^n$ are compared. The vector with the "less uniformly distributed" components is said to be majorized by the other. Specifically, with their components arranged in descending order, \mathbf{y}_1 is majorized by \mathbf{y}_2 , and written as $\mathbf{y}_1 \prec \mathbf{y}_2$, if

$$\left\{ \begin{array}{l} \sum_{i=1}^k y_{1i} \leq \sum_{i=1}^k y_{2i} \quad \text{for } k = 1, \dots, n \text{ and} \\ \sum_{i=1}^n y_{1i} = \sum_{i=1}^n y_{2i}. \end{array} \right.$$

An equivalent *weak* statement, denoted by \prec^w , is possible if the total equality condition does not hold. This has long been known in econometry and mathematics [16] and extensions to functionals which preserve such properties have also been developed.

Proposition 1 [15] *The inequality*

$$\sum \phi(y_{1i}) \leq \sum \phi(y_{2i})$$

holds for all continuous decreasing convex functions $\phi(\cdot)$ iff $\mathbf{y}_1 \prec^w \mathbf{y}_2$. ■

¹One can show that any convex/concave function which is monotone over an interval of interest can be order-preserving and thus be fully adequate.

²A parent segmentation consists of a twinned (or merged) version of two children segmentations.

One such functional which is also encountered in information theory is the entropy criterion $\phi_1(x) = -x \log x$. The notion of parsimony of a signal representation was also shown to be tightly linked to its complexity [12] and is therefore a useful basis for a BB search metric.

Although this has been widely successful for a large class of problems, we can observe from Figure 1 that the distinction among the ECG segments involves not only amplitude but also smoothness and curvature information which we respectively denote by $\delta(x)$ and $\kappa(x)$. This is addressed below.

3. FEATURE-DIRECTED BB SEARCH

Parsimony is clearly an important attribute for any representation. However, the morphological features which are visually manifest turn out to be crucial to an initiated ECG interpreter and thus indispensable for any automatic segmentation. Towards that end, we construct a criterion which combines the expected smoothness/curvature measure $\phi_2(x)$ of the signal with an entropy-like measure which reflects the “best” (most parsimonious) representation measured by $\phi_1(x)$. The mathematical properties enjoyed by the functionals $\phi_1(\cdot)$ and $\phi_2(\cdot)$ allow us to construct $\phi_s(x)$ and carry out the bottom-up search on the dyadic tree with the efficiency commonly associated with binary tree searches (i.e. $O(K \log K)$ operations). This framework, albeit deterministic, may be viewed as a statistical Bayesian framework similar to that developed in [14] with the difference here, that the additional morphological constraints play the role of a penalizing prior, or

$$\phi_s(x, \{\mathcal{W}_{i,(\cdot)}\}) = \phi_1(\{\mathcal{W}_{i,(\cdot)}\}) + \lambda \phi_2(\kappa(x), \delta(x)), \quad (2)$$

where the parameter λ is adjusted to enforce/alleviate the penalizing influence of κ and δ . Note that up to this point *no* heuristic information is employed other than the basic signal analysis concepts embodied in the criterion.

Note that a second step to our algorithm may be required on account of the inherent limitations imposed by the orthogonal transform. Given the non-invariance in time of the orthogonal transform and the dyadic constraint imposed by the need for search efficiency, we are faced with a choice of “a best segmentation” in a class \mathcal{S} of segmentations resulting from a set \mathcal{J} of initial resolutions. This can be viewed as an optimization over \mathcal{S} . One can for instance use ideas from [13] to select the *most time-invariant* representation of the segmentation with an associated lowest cost $\phi_s(\cdot)$ over \mathcal{J} .

3.1. Novel Segmentation Criterion

As will be later illustrated, the usual entropy criterion is insufficient for an acceptable ECG signal segmentation. To alleviate this limitation, we conjecture that visual discrimination of the ECG segments employs not only amplitude but also smoothness and curvature (at least first and second derivative) information. We propose, as a result, a criterion which reflects not only the parsimony of the signal representation but also its smoothness/curvature. Our new criterion thus combines an appropriately constructed function of the expected smoothness/curvature of the signal with an

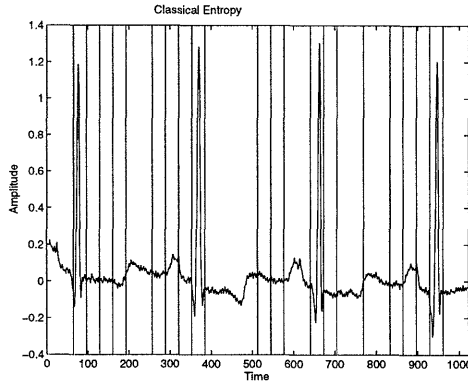


Figure 2: Example of failed segmentation based on pure entropy criterion.

entropy-like measure which reflects the “best” (most parsimonious) representation. As briefly noted earlier, the ECM which reflects the parsimonious representation will tend to oversegment the ECG signal and thus obscure the desired features of the various cardiac waves. Following the developments in [11, 6], we define the functions $w_{j,k}(t)$ in an interval I_j for $j \in \mathcal{Z}$. For efficiency sake, we choose the intervals and the total support T (observation interval) of signal $x(t)$ to be dyadic. That is to say that if we denote $\text{span}\{w_{j,k}(t)\} = \mathcal{B}_j$, we then establish that the functions

$$w_{j,k'}(t) = \frac{\sqrt{2}}{|I_j| + |I_{j+1}|} g_j(t) \cos \left[\pi(k' + 1/2) \frac{t - t_j}{|I_j| + |I_{j+1}|} \right], \quad (3)$$

are in $\tilde{\mathcal{B}}_j$, with $0 \leq k' \leq |I_j, I_{j+1}| - 1$. By denoting the corresponding sets of coefficients of $x(t)$ by $\{\mathcal{W}_{j,k}\}$ and $\{\mathcal{W}_{j+1,k}\}$, we proceed to construct a search criterion to

- Account for the simplest representation of the ECG signal via an entropy function $\phi_1(\mathcal{W}_{(\cdot, \cdot)})$
- Account for the morphology of the signal smoothness/curvature by using $\kappa(x)$ and $\delta(x)$ defined earlier in the cost functional $\phi_2(\kappa(x), \delta(x))$ in Eq. 2

The functional $\phi_2(\cdot)$ is chosen to be convex and order-preserving (i.e. for weak majorizations of sequences). It is a penalizing factor for lack of smoothness, which when combined with $\phi_1(\mathcal{W}_{(\cdot, \cdot)})$ forms the basis of our search criterion, with λ as a parameter selected to adjust the penalty enforcement. The comparison/selection process thus depends on the significant intrinsic features of the signal itself. The search index set \mathcal{J} is a control parameter which is used to determine the degree of refinement of the segmentation, and the output is a small set of segmentations of the signal.

4. EXPERIMENTAL RESULTS

In Fig. 2, we show a segment of consecutive heartbeats from a long data recording from the MIT ECG data base. The entropy criterion originally proposed (i.e. $\phi_1(x) = -x \log x$)

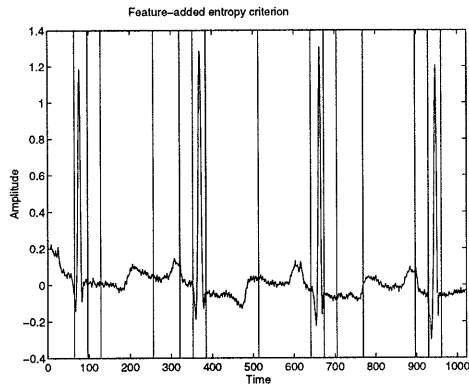


Figure 3: Feature-added entropy criterion

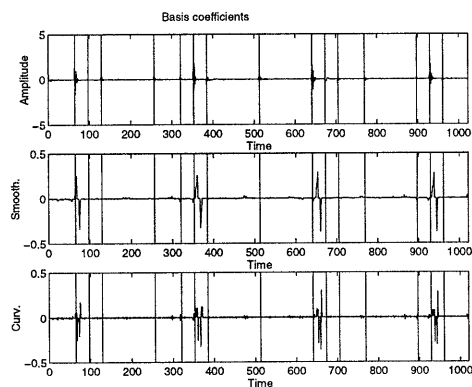


Figure 4: Feature-directed Segmentation

which ensures parsimony of representation, results in a segmentation which is clearly too dense for a typical ECG waveform segmentation. We then add the penalizing factor embodied in $\phi_2(x)$, with e.g., $\phi_2(x) = \exp(-x)$. This functional applied on κ and δ , allows us to guide the BB search with the *best* approximate emulation of the human visual system. This is shown in Fig. 3, and the distribution of the coefficients as well as quantitative smoothness/curvature are shown in Fig. 4.

5. CONCLUSION

The preliminary results obtained with this novel approach to ECG analysis are very encouraging. This approach, so far as we know, is a departure from the existing techniques, and has a clear advantage over what is available. A number of outstanding issues remain to be resolved, in particular the constraints present in the dyadic framework of orthonormal bases, etc.

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