Improvement of QRS Boundary Recognition by Means of Unsupervised Learning

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Abstract

Most of the ECG wave boundaries detection algorithms are based on the matching of an one-dimensional detection function against a standard template computed from an expert controlled reference data set. In this paper, we propose to enhance the method by first stratifying the shapes of the detection functions in the vicinity of the waveform boundaries into K shape specific classes Cj (j=1,K) by means of a Kohonen self-organizing neural network. We then compute a matching template for each category Cj and we extend the standard wave delineation algorithm to take account of these new templates. The method has been assessed on the CSE databases DS1 and DS3 for the determination of the onset of QRS.

1. Introduction

One of the most important ECG signal processing steps before feature extraction and diagnostic classification is waveform segmentation and boundary recognition, e.g. the estimation of the onsets and end points of the P, QRS and T waves. As for image processing, there is no standard or optimal way to estimate these wave boundaries. The most commonly used methods are threshold crossing, signal matching and template matching [1]. The latter consists in mapping the multi-dimensional time-varying ECG signals into a new one-dimensional time-varying detection function and then in matching this detection function with an amplitude-time template within some W(-M,N) window around the point where the boundary is expected [2]. The most widely used detection function is the "spatial velocity". Assuming that the sampling rate is 500 samples/sec, then the most efficient detection function is the filtered spatial velocity SV(i) computed as follows [2]:

\[ SV(i) = \left( \sum_{k} X'_k(i)^2 \right)^{1/2} \text{(in } \mu \text{V/ms)} \]

where \( r \) is the number of ECG leads and

\[ X'_k(i) = \frac{[2(X_k(i+4)-X_k(i-4))+X_k(i+2)-X_k(i-2)]}{40} \]

For the stratification of the shapes of the detection functions, we then select a segment X of n points of SV(i) centred around the fiducial point we want to detect. These segments X form an n-dimensional vector that will constitute the inputs of the artificial neurons of the Kohonen network.

2. Materials and Methods

2.1. Artificial neural networks inputs determination

ECG and VCG signals are usually recorded using 3 or more leads simultaneously. For wave onset and end detection purpose, computer programs take advantage of this redundancy to map the multilead signal into a one-dimensional time-varying detection function d(i) (i the sample number). The artificial neural networks inputs are determined as follows [2]:

\[ SV(i) = \left( \sum_{k} X'_k(i)^2 \right)^{1/2} \text{(in } \mu \text{V/ms)} \]

where \( r \) is the number of ECG leads and

\[ X'_k(i) = \frac{[2(X_k(i+4)-X_k(i-4))+X_k(i+2)-X_k(i-2)]}{40} \]

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2.2. Stratification of the shapes of the detection functions by means of Kohonen self-organizing maps

Let us note E the number of ECGs constituting the unsupervised learning set, \( x_1, x_2, ..., x_E \) the values of the detection function corresponding to the n points of segment X, \( X(x_1, x_2, ..., x_E) \) the inputs to the Kohonen network and \( W_k(w_{k1}, w_{k2}, ..., w_{kn}) \) the weights of the synapses arriving on neuron k (figure 1).
The network consists in an input layer of n input neurons and in an output layer of S output neurons [3]. S is usually chosen to be greater or equal to the number E of cases forming the learning set. The basic concept of the Kohonen algorithm then consists in associating each input to a class Cj and to display the output neurons in an output layer of S output neurons. S is usually chosen to be greater or equal to the number E of cases forming the learning set. The basic concept of the Kohonen method is the following:

**Parameters initialisation**

1. Determination of the form (p,q) of the Kohonen map, the number of output neurons S=pxq, and the maximum number of iteration steps tmax.
2. Initialisation of the weights wj, (k=1,S, j=1,n) of the output neurons (small random values).

**Kohonen algorithm**

1. For ECG record X, choice of the winning neuron k such as:
   \[ \| W_k - X \| \leq \| W_j - X \|, \quad j = 1,S \]
2. Adaptation of the learning parameters \( \alpha(t) \) and \( V(j,k,t) \), where:
   \( \alpha(t) \) is a linearly decreasing learning function defined by:
   \[ 0 < \alpha(t) < 1, \quad \alpha(t) = \alpha_0 / (1 + k_u \cdot t) \]
   \( \alpha_0 \) is a constant, the learning rate \( k_u \) is constant
   \( V(j,k,t) \) is a continuous neighbourhood function modelled by a Gaussian:
   \[ V(j,k,t) = \exp[-\sigma^2(j,k)/2\cdot\sigma^2(t)], \]
   where:
   \( \sigma(t) = \sigma_0 / \sigma_0^{\text{min}} \)
   \( d(j,k) \) is the city-block distance between the neurons j and k; \( \sigma_0 \) and \( \sigma_1 \) are constants.
   The amplitude of \( V \), determined by \( \sigma^2(t) \), decreases as the network reaches convergence.
3. Adaptation of the neuron weights:
   \[ W_j(t+1) = W_j(t) + \alpha(t) \cdot V(j,k,t) \cdot [X - W_j(t)] \]
4. Set \( t = t+1 \) and go to step 1 until \( t > t_{\text{max}} \).

The amplitude of \( V \), determined by \( \sigma^2(t) \), decreases as the network reaches convergence.

**Signal matching algorithm**

Signal matching assumes that we first compute a standard waveform \( t(k) \) from a learning set of E detection functions \( SV(k) \) with known fiducial points. The method then tries to fit a \([-M,N]\) time-window of an unknown function \( SV(i) \) with template \( t(k) \) and searches for the minimum \( i_0 \) of the matching function \( MF(i) \) within a given time interval [2]:

\[
MF(i) = \sum_{k=0}^{N} \frac{[SV(i+k) - t(k)]^2}{w^2(k)}, \quad -M < k < N
\]

where \( w^2(k) \) is a weighting function usually computed as being the variance of the learning set detection functions at point k.

Point \( i_0 \), for which \( MF(i) \) is minimum, will be taken as boundary. The algorithm then searches [2] for the first local maximum \( H \) and minimum \( L \) following \( i_0 \). This procedure is eventually repeated until finding the first local minimum which satisfies the following three criteria:

(i) \( MF(L) < R \) where \( R = 14(N + M + 1) \mu V \)
(ii) \( MF(L)/MF(i_0) < 15 \)
(iii) \( |L-H| > 12 \text{ ms} \)

If no local minimum \( L \) satisfying these criteria is found, \( i_0 \) is retained.

**2.4 Learning and Test sets**

In this paper, we present only the results for the determination of QRS onset. For training, we have used the 125 first ECGs of the so-called CSE artificial ECG library Data Set 1 (DS1). For testing, we have used both the 155 ECGs of CSE DS1 (125+2*15 « repeated » beats) and the 123 ECGs of Data Set 3 (DS3) of the CSE Multilead Database.

The detection functions \( SV(i) \) were computed from the orthogonal \( (X,Y,Z) \) components of the 15-Lead ECG signals. Segment X was empirically selected by taking the 51 sample points before the first spatial velocity peak of the filtered detection function.

The templates were computed from DS1 by taking the CSE referees waveform recognition points as the golden standard.
3. Results

3.1. Training set (DS1) results

At the end of the classification of CSE DS1 we obtained 6 classes that are displayed hereafter in figure 2. Figure 3 displays the output neurons weights for two different values of the learning factor $\sigma_t$. For $\sigma_t=2.5$, each class $C_j$ is represented by one single neuron. The weights of the other 138 output neurons are almost close to zero (figure 3b). For $\sigma_t=0.5$, much more output neurons are elected during the Kohonen unsupervised learning process (figures 2a and 3a). The classification results interpretation is more complex. It requires a visual interpretation and the design of some decision rules to regroup the different winners by defining class centers and the maximum admitted distance to assign an output neuron to the class represented by the class center.

![Figure 2. (12x12) Kohonen map of DS1, for $\sigma_0=1$, $\sigma_0=22$, $k_0=0.01$, $t_{max}=4000$ and for two different $\sigma_t$ values.](image)

![Figure 3. Weight vectors for two different values of $\sigma_t$.](image)

Table 1 shows the optimal template windows dimensions for each class $C_j$.

<table>
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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
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<td>4</td>
<td>3</td>
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<td>7</td>
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</tbody>
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Table 1: Template windows dimensions. $M$ and $N$ respectively yield for the number of sample points before and after QRS onset and end.

Figure 5 and 6 display the templates computed from DS1 and the histogram of the sample points differences between the template matching results and the referees references. The standard deviation SD for the whole Data Set 1 (N=155) is only 3.28 ms.

3.2. Test set (DS3) results

The number of cases respectively assigned to classes $C_j$, $j=1,6$, are 16, 3, 18, 58, 7 and 23. The onset of QRS delineation errors are presented in figure 7. Standard
deviation SD=4.59 ms (N=123).

Figure 4. Error between input data X and the weights of the winners for two values of \( \sigma_f \). The horizontal axis represents the number of times each input vector has been classified (maximum is 4000/125=32).

Figure 5. Spatial velocity templates constructed from DS1. The vertical line denotes the QRS onsets determined by the CSE referees. The horizontal axis is graduated in sample points (2 ms differences).

4. Conclusion

Using unsupervised learning to stratify the detection functions significantly improved (~20%) the precision of the determination of the onset of QRS. Our work thus could encourage further studies to improve the determination of the other fiducial points then the onset of QRS. A more precise determination of the exact number of detection function classes would however require much larger databases than CSE DS1 and DS3.

References


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