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 (i=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 template is constructed from a learning set of E detection functions stemming from E different ECG recordings in which the wave boundaries have been recognized by human observers. The main limitation stems from the fact that such a template can only imperfectly represent the vast diversity of ECG waveform shapes.

In this paper, we propose to stratify 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 and then to compute a matching template for each category Cj. Then, in routine use, we first classify each ECG detection function into one of the Cj categories determined by the Kohonen network (unsupervised learning) and we identify the waveform boundary by matching the ECG detection function against the template corresponding to category Cj.

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 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]:

$$SV(i)=\left(\sum (X'_k(i))^2\right)^{1/2} \text{ (in } \mu v/ms),\ k=1,r$$

where r is the number of ECG leads and

$$X'_k(i)=[2(X_k(i+4)-X_k(i-4))+X_k(i+2)-X_k(i-2)]/40$$

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.

2.2. 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, $x_1,..,x_n$ the values of the detection function corresponding to the n points of segment X, $X(x_1,..,x_n)$ the inputs to the Kohonen network and $W_k(w_{k1},..,w_{kn})$ the weights of the synapses arriving on neuron k (figure 1).

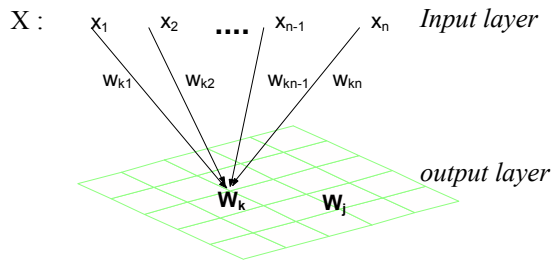

Figure 1. 2D Kohonen map with pxq=36 output neurons.

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 according to a 2D map that highlights the similarities between the different classes. Inputs that are similar in the representation space will activate output neurons that are neighbours in the 2D map. In analogy with other standard automated classification methods, depending on the value of a learning parameter σ_f, when there are K classes, at the end of the training there will be either K output neurons or K groups of output neurons that will be activated. The Kohonen algorithm has self-organizing and input space topology representation properties.

The basic steps of the Kohonen method are 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 w_{kj} (k=1,S, j=1,n) of the output neurons (small random values).

Kohonen algorithm

1. For ECG record X, choice of the winner neuron k such as:
   $\| W_k - X \| \leq \| W_j - X \|$, j =1,S
2. Adaptation of the learning parameters α(t) and V(j,k,t), where:
   α(t) is a linearly decreasing learning function defined by:
   $0 < \alpha(t) < 1$, $\alpha(t) = \alpha_0 / (1 + k_\alpha t)$
   α_0 is a constant, the learning rate k_α is constant
   V(j,k,t) is a continuous neighbourhood function modelled by a Gaussian:
   $V(j,k,t) = \exp[-d^2(j,k)/2.\sigma^2(t)]$, where:
   $\sigma(t) = \sigma_0.(\sigma_f / \sigma_0)^{t/tmax}$, d(j,k) is the city-bloc distance between the neurons j and k; σ_0 and σ_f are constants.
   The amplitude of V, determined by $\sigma^2(t)$, decreases as the network reaches convergence.
3. Adaptation of the neuron weights:
   $W_j(t+1) = W_j(t) + \alpha(t).V(j,k,t).[X - W_j(t)]$
4. Set t=t+1 and go to step 1 until $t > t_{max}$

(presentation of another sample of the learning set; adaptation of the parameters α(t) and v(j,k,t), ….)

The number of elements composing class Cj is obtained by counting and adding the number of times each output neuron corresponding to class Cj has been elected.

2.3. ECG wave boundaries recognition

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]:

$$MF(i) = \sum_{-M}^{N} [SV(i+k) - t(k)]^2 / w^2(k), \qquad \textbf{(2)}$$

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) μv
(ii) $MF(L)/MF(i_0) < 15$
(iii) $|L-H| > 12$ 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 σ_f. For $\sigma_f = 2.5$, each class Cj is represented by one single neuron. The weights of the other 138 output neurons are almost close to zero (figure 3b). For $\sigma_f = 0.5$, 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.

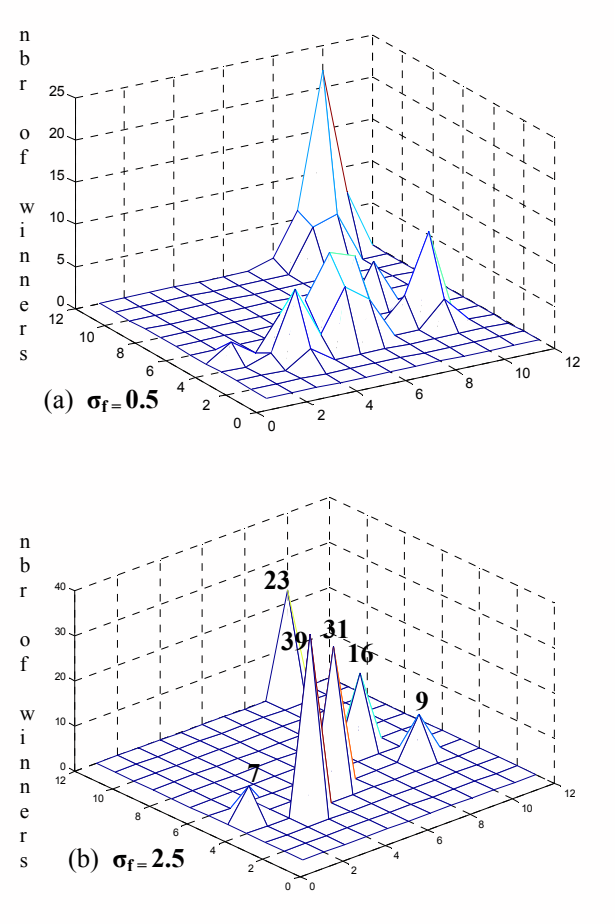

Figure 2. (12x12) Kohonen map of DS1, for $\alpha_0 = 1$, $\sigma_0 = 22$, $k_\alpha = 0.01$, tmax=4000 and for two different σ_f values.

Figure 4 presents the error curve of the differences between the input data and the weights of the winning neurons in function of the number of iterations for two values of σ_f. At the beginning, the error values are almost identical, but then the error values decrease as more and more output neurons are selected by the classification process.

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

class	1	2	3	4	5	6
M	3	6	3	3	4	8
N	4	4	3	2	4	7

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.

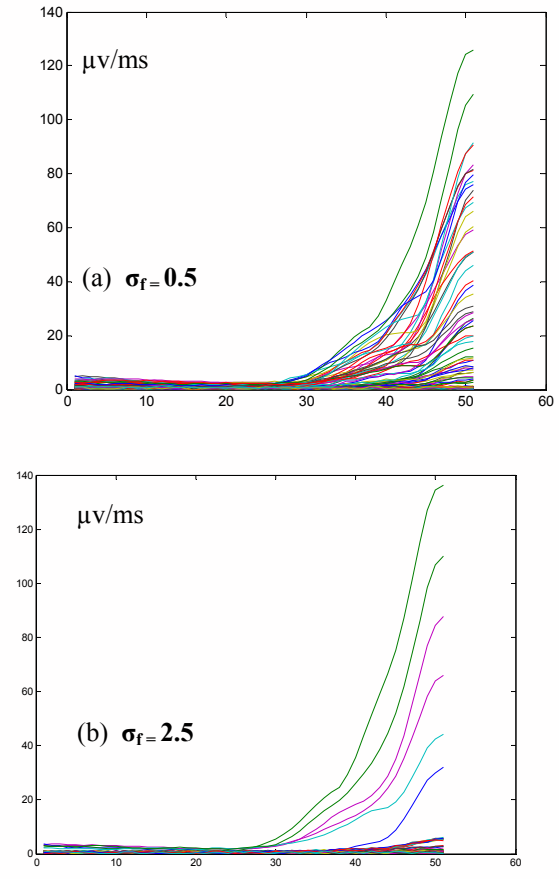

Figure 3. Weight vectors for two different values of σ_f .

3.2. Test set (DS3) results

The number of cases respectively assigned to classes Cj, 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 is 4.59ms (N=123).

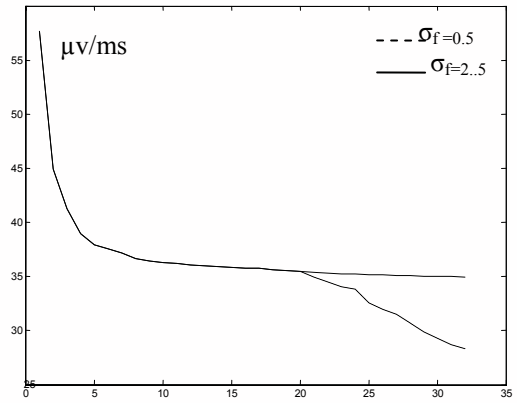

Figure 4. Error between input data X and the weights of the winners for two values of σ_f. The horizontal axis represents the number of times each input vector has been classified (maximum is 4000/125=32).

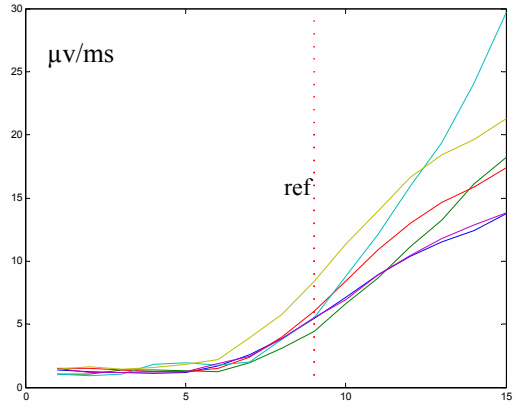

Figure 5. Spatial velocity templates constructed from DS1. The vertical line denotes the QRS onsets determined by the CSE referees. The horizontal axis is graduated in sample points (2 ms differences).

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.

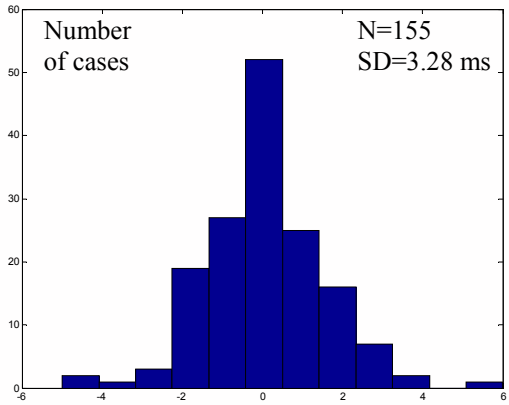

Figure 6. Onset of QRS delineation errors for DS1

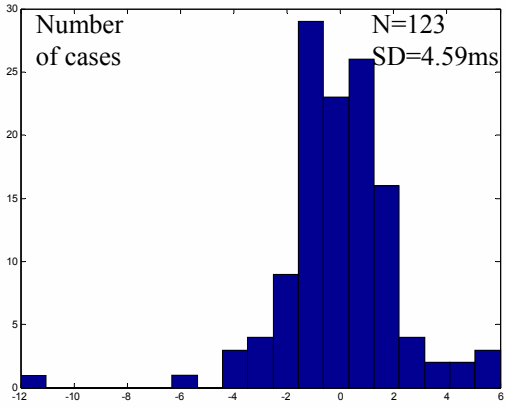

Figure 7. Onset of QRS delineation errors for DS3

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