New method for QRS-wave recognition in ECG using MART neural network

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Recognition of QRS-Wave in the ECG signal is one of the important stages for ECG signal processing and most of the ECG noise removal algorithms, and automatic ECG interpreter systems need to detect these points. In most cases ECG signals are noisy and we need to detect these points using noisy signals. We have developed a QRS-wave recognition system using MART (multi-channel ART) neural network. In this method signal of two leads of ECG is used for detection, so our method has low sensitivity to noises. We tested our method for noiseless and noisy ECG signals and we compared results against those of an older one, which uses ART2 neural network. Results showed that our method has good results for noisy signals.

1 Introduction

Recording of electrocardiograms (ECG's) is a useful tool for diagnosing heart disease. Typical cycle of an ECG is shown in Fig. 1. Based on ECG signal shape and distance between fiducial points and other parameters, physicians diagnose heart diseases. Recognition of the fiducial points and calculation of parameters is a tedious routine for the physician; 100000 cardiac cycles per patient are recorded in a day and a physician has to interpret this large amount of ECG data to search for only a few abnormal cardiac cycles in the ECG. Therefore there is an urgent need for an automatic ECG interpreting system to help reduce the burden of interpreting the ECG. As it is evident, ECG interpreting systems must first locate fiducial points and then calculate parameters. So precise recognizing of the fiducial points such as QRS points is very important for automatic ECG interpreting system. In the other hand most of ECG noise removing algorithms for example EMG noise removing algorithms, need to recognize QRS points first [1], [2]. These algorithms need to recognize QRS-wave from noisy signal, so precise locating of these points results good noise cancelling property. The first stage for QRS-wave recognition is the detection of R point. After the detection of R point ECG signals are segmented into cardiac cycles and Q and S point are detected in each cardiac cycle with respect to R point. In [3] after detection of R Points, cardiac cycles in the duration of 10s are stacked one over another to reduce noise, and using "slope detection " method, Q and S points are detected. But the Q and S points detected by this method are the averages of Q and S of stacked cardiac cycles. Neural networks are another known method for processing ECG data [4], [5]. In [4] a trained ART2 network is applied to locate Q and S points. In this paper we use MART neural network for locating Q and S points. The main feature of this network is the use of multiple channels of ECG data for recognizing Q and S points resulting in a low sensitivity to noise. In this work both ART2 and MART methods are implemented and the results are compared.

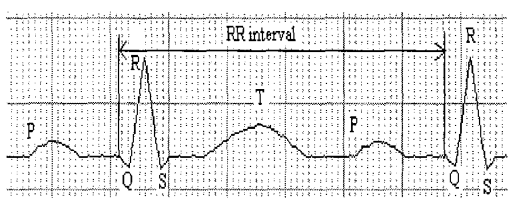

Figure 1: Typical cardiac cycle and fiducial points

2 Preprocessing

ECG's are often contaminated by disturbances such as power line frequency components and baseline wander. The preprocessing stage removes these noises from ECG and detects R points in ECG. One method for removing power line noise and baseline wander is the application of digital filters. IIR filters of [6], [7] and FIR filter of [8], [9] and adaptive filter of [10] can be used for removing power line noise and baseline wander. We used the Kaiser window based FIR filter for this purpose.

2.1 Detection of R point

After removing baseline wander and power line noise from ECG, the R point is detected. After detection of R point ECG are divided into cardiac cycles. One cardiac cycle is from one R point to another. For detecting R points ECG signal is filtered using high pass and low pass filters. These two filters constitute a band pass filter, which removes frequency components that are not part of QRS-complex. Equations for low pass and high pass filters, are given by

$$y(nT)=2y(nT-T)-y(nT-2T)+x(nT)-2x(nT-6T)+x(nT-12T) \quad (1)$$

$$y(nT)=y(nT-T)-x(nT)/32+x(nT-16T)-x(nT-17T)+x(nT-32T)/32 \quad (2)$$

After the band pass filtering, the output of filter is differentiated. The difference equation, for differentiating ECG is given by

$$y(nT)=(2x(nT)+x(nT-T)-x(nT-3T)-2x(nT-4T))/8 \quad (3)$$

Then the squaring function squares each differentiated ECG data. Finally the time averaging is carried out over the 32 most recent values of ECG resulted from the squaring function. For locating R point, peak detection algorithm is applied to the time-averaged signal, but simple peak detection algorithm detects many local peaks so other consideration is required [11].

3 Locating Q and S points using ART2 neural network

To recognize QRS-wave using ART2 network, the algorithm assumes that the portion of ECG from the R point to Q point and the portion of ECG from R point to S point can be approximated by a straight line. This is only a preliminary assumption. After learning take place with the ART2 network, this assumption will be released. So ART2 network is trained by triangle like inputs with height of 1 and variable base of between 0 and 100ms. The number of input patterns, for training depends on sampling period T. For example for T=2ms, 50 patterns are required. After detection of R point, two 100ms ECG data from the R point to the S point and from the R point to the Q point are normalized between 0 and 1. Then these normalized data are given to ART2 network for detection of S and Q points. ART2 neural network selects pattern that is closest to input pattern. ART2 output is an approximation of Q and S point. For precise determining of Q and S points, the recognizer of system establishes search regions for Q and S points, i.e. 4ms before and after the points indicated by ART2 network. The recognizer considers a location of ECG as the Q point when the slope (x(nT)-x(nT+T))/T is less than 16.0 in the Q point search region, where T is the sampling rate of the ECG. The S point is the location where the following condition is satisfied.

$$(x(sT+nT)-x(sT+nT+T))/T = \begin{cases} <0 & n=-2,-1,0 \\ >0 & n=1,2 \end{cases} \quad (4)$$

Where s is the location of S point in search region. If there is no location satisfying the above condition, the system assumes that the approximate locations indicated by ART2 network are the Q and S points respectively. If there are a few points satisfying above condition, system may recognize a point as the Q and S point that is not the true Q or S point. The modified ART2 network used for recognizing Q and S point is different from traditional ART2 network. In this network after selection of a pattern by ART2 network, reset signal is sent to corresponding cluster when one of the following cases occurs. First when $\|r\|<\rho$ (vigilance parameter check) and second when the area of dashed region in figure 2 is greater than a threshold. This threshold is 1.2 for Q point and 1.75 for S point.

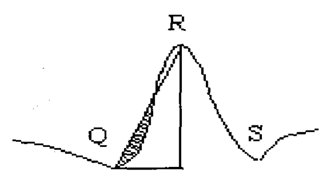

Figure 2: Area between selected triangle and ECG

4 MART neural network

MART or multi-channel ART network, which is introduced by M. Fernandez-Delgado and S. Barro Ameneiro, [12] is similar to ART2 network, but MART network is a multiple channel neural network and uses information of multiple channels for classification and pattern recognition. In this section we describe this network briefly.

4.1 An overview of MART

In fig. 3 block diagram of MART network is shown. MART network has following parameters

- d — Global difference between the input pattern and the template for the winning category.
- d_i — Difference between the input pattern and the template for winning category in channel i.
- I — Number of signal channels.
- I_i — Input pattern in channel i: $I_i=(I_{i1}, ..., I_{iJ})$.
- J — Number of nodes in the F1 layer of each block, i.e., number of pattern points in each channel.
- K — Number of nodes in the F2 layer of each block and the F3 layer.
- P_k — Global similarity between input pattern and the category k template.
- ρ_g — Global vigilance parameter of the orienting system.
- ρ_a — Template updating vigilance parameter.
- T_{ik} — Similarity between the input pattern and kth category template in channel i.
- x_i — Credibility of channel i.

The MART network consists of I blocks (each block i consisting of two layers of fully interconnected nodes, $F1_i$ and $F2_i$), the third node layer F3 and an orienting system bridging between the $F1_i$ layers and F3. In each single-channel block i, each node in layer $F1_i$ is connected to each node in $F2_i$ by a two-way link. The upward link between $F1_{ij}$ (the jth F1 node in channel block i) and $F2_{ik}$ (the kth F2 node in channel block i) is associated with a value Z_{ijk} and the downward link is associated with a weight Z'_{ijk} that is numerically the same as Z_{ijk}. Each node $F2_{ik}$ is also connected by an unweighted two-way link to node $F3_k$ (the kth node of F3 layer). In the orienting system, channel i node receives input from each of the nodes in $F1_i$ and has a single output line to the global node Re, which sends out a signal to the nodes in F3 which can be used for inhibitation of the F3 nodes.

For classification of an input pattern by MART, the input pattern for each channel i, $I_i=(I_{i1}, \ldots, I_{iJ})$, enters into the classifier via the $F1_{ij}$ nodes and is compared with the templates associated with the $F1_i$ -$F2_i$ connections. The upward output of the layer $F2_i$ to $F3_k$, T_{ik} is calculated by following equation.

$$T_{ik} = J - \sum_{j=1}^{J} | I_{ij} - Z_{ijk} | \quad i = 1,..., I, \; k = 1,..., K \quad (5)$$

In F3 layer, T_{ik} values, which are sent up from the channel i nodes in $F2_{ik}$, are summed to give the global similarity between the current input pattern and the current template for category k, i.e., $P_k=\sum T_{ik}$. $F3_k$ node has another input, which is labeled as re_k in fig. 3. This input is a binary signal from the global orienting node Re; when zero, it has no effect, but when set to unity it totally inhibits $F3_k$. After the calculation of P_k, k^*, the uninhibited node with largest P_k is selected as node, wining competition. If there isn't any uninhibited node, new category is created and the input pattern is assigned to it. In any way the output of $F3_{k^*}$ is sent down to the F2 layer and then to the F1 layer and the orienting system. Equations for this down processing are as follows, where V_{ij} values are the outputs of $F2_i$ layer and d_{ij} and d_i are input and output of the $F1_i$ layer respectively.

$$V_{ij} = Z'_{ik^*j} \qquad d_{ij} = | I_{ij} - Z'_{ik^*j} | \quad (6)$$

$$d_i = \frac{1}{J} \sum_{j=1}^{J} d_{ij} \quad (7)$$

The outputs of F1 layer i.e., d_i are sent to orienting system, orienting system calculates weighted average of d_i, $d=\sum x_i d_i$, where the weights x_i used to calculate d, evolves in accordance with the credibility accumulated by channel i during classification. If $d<\rho_g$, the input pattern is accepted and learning process is performed. If $d>=\rho_g$, $F3_{k^*}$ is inhibited by setting re_{k^*} to one, and assignment cycle repeated as described. This cycle is repeated until either a category is found with enough similarity (in this case the pattern is assigned to this category, whose template may be trained), or the set of currently recognized category exhausted (in which case the new category is created and input pattern is assigned to it).

4.2 MART network learning equation

The initial value of each Z_{ijk} and Z'_{ijk} is 1/(J+1). When an input pattern accepted as k^*th category i.e., $d<\rho_g$, Z_{ijk} and Z'_{ijk} may be updated. For updating Z_{ijk} and Z'_{ijk}, the pattern must satisfy stricter similarity criterion than is applied by orienting system, namely $d<\rho_a$, where $\rho_a<\rho_g$. For complete description of MART network learning equations, reader can refer to [12].

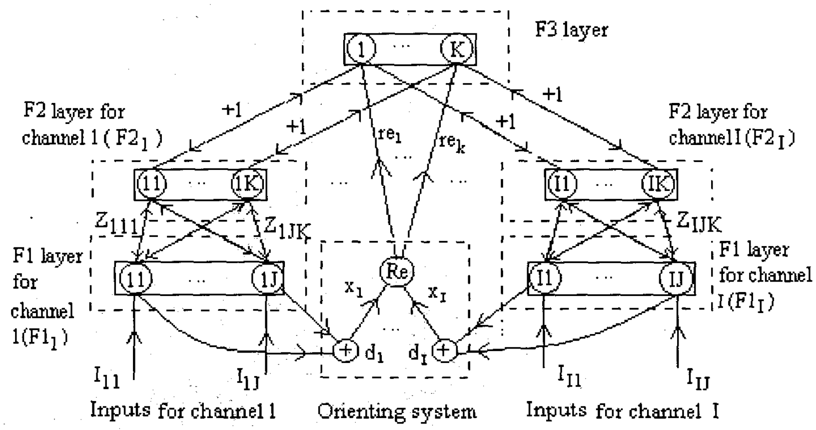

Figure 3: Complete structure of MART

5 Locating Q and S points using MART network

To locate Q and S points by MART network, we used a two-channel network. Similar to ART2 network, MART network is trained by triangle-like patterns for both channels. In orienting system of the modified MART network, we also check the condition of the area between the selected triangle and ECG, as described before, but for both areas where ECG is greater or smaller than the selected triangle. If neither of the channels satisfies these conditions the selected cluster is inhibited. But if one of the channels satisfies the area conditions the selected cluster is acceptable.

6 Results

We tested two methods of locating Q and S points with noiseless and noise-added MIT-BIH data. For training of ART2 network we used slow learning method [13] with ρ=0.9999 and 2000 epochs of training. With this vigilance parameter ART2 network can learn any of the triangle like patterns as different category. After the training of triangle like patterns, ρ is set to 0.98 for recognition. For MART network we used the following parameters.

$I=2$ $\quad x_i=\frac{1}{I}$ $\quad \delta_1=0.05$ $\quad \delta_2=0.15$

$\delta_3=0.25$ $\quad A_z=0.75$ $\quad A_l=0.75$ $\quad r_{\max}=0.3$

$B_1=0.75$ $\quad B_2=0.25$ $\quad \rho_g=0.15$ $\quad \rho_a=0.1$

Table 1,2 show results of the detection of Q point for approximately noiseless and clean data and the results for S point are similar to those of Q point. As it is evident, the ART2 network has nearly good results. The reason is that data are noiseless and the ART2 network has better resolution for pattern separation than MART network (As our tests showed). In the other test after R point detection, we added sinus noise with varying amplitude to ECG data of one of the channels. As the amplitude of noise increases, the MART network results are more desired with respect to ART2. Table 3,4 show results for sinus noise with maximum amplitude of 0.4, which is added to the normalized ECG data. The MART network results for this type of data are better than ART2 results.

Table 1: Detection of Q points using ART2 networks for noiseless data

Data Type	Recognition error for ART2 (ms)					
	0	2	4	6	8	More than 8
1	97	16	5	2	0	0
2	102	8	10	0	0	0
3	105	6	9	0	0	0
Total	304	30	24	2	0	0

Table 2: Detection of Q points using MART networks for noiseless data

Data Type	Recognition error for MART (ms)					
	0	2	4	6	8	More than 8
1	80	23	11	3	3	0
2	94	11	12	2	1	0
3	103	11	4	2	0	0
Total	277	45	27	7	4	0

Table 3: Detection of Q points using ART2 networks for noisy data

Data Type	Recognition error for ART2 (ms)					
	0	2	4	6	8	More than 8
1	2	4	28	50	26	28
2	3	5	30	47	27	26
3	4	5	26	49	26	28
Total	9	14	84	146	79	82

Table 4: Detection of Q points using MART networks for noisy data

Data Type	Recognition error for MART (ms)					
	0	2	4	6	8	More than 8
1	34	28	24	30	20	2
2	38	26	20	31	22	1
3	32	29	25	28	24	0
Total	104	83	69	89	66	3

7 Conclusion

In this work we introduced new method for recognizing QRS-wave using MART network and we compared it with ART2 network. The MART network uses two channels of data for detection of Q and S points and more channels can be used too. For comparing two methods with each other, we used both clean and noisy ECG data. Experimental results show that MART network has very good results for noisy data. But for clean ECG, ART2 results are a little better than MART results, although MART results are also good. For using these algorithms in real world systems and precise recognizing of QRS-wave, our recommendation is that the system can detect noise level of ECG. For low noise ECG, system can use ART2 network and for noisy ECG, MART network should be used.

8 References

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