Paper

Extraction of the QRS Wave in an Electrocardiogram by Fusion of Dynamic Programming Matching and a Neural Network

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We propose a method to extract the QRS wave in an electrocardiogram (ECG). It is extracted by detecting two characteristic points (CPs), the Q and S points. There are two main problems that make detection of CPs difficult: 1) noise contaminating the ECG and 2) individual variation of waves and complexes in the ECG. We use DP matching for overcoming the problem of noise contamination and a neural network of ART2 for overcoming the problem of individual pattern variation. These two methods are fused using a multichannel ART-based neural network (MART) for reliable detection of CPs. The method was evaluated using an MIT/BIH arrhythmia database. It was found that the rates of accuracy within 6 ms error were 99.6% for S point detection and 96.4% for Q point detection, indicating that the present method has good potential for detection of CPs on an ECG.

Keywords: electrocardiogram (ECG), QRS wave, DP-matching, ART2, MART, Fusion

1. Introduction

An electrocardiogram (ECG) is a record of the electrical potential induced by heart beats, which is recorded by attaching small electrodes on the body (Fig. 1). Since recording an ECG is simple, noninvasive, and inexpensive procedure, it is widely used to diagnose heart diseases [1][2]. For a precise diagnosis, the ECG is recorded for a whole day with a Holter device that records an ECG of more than 100,000 cardiac cycles. A reliable ECG analyzer is needed to analyze such a large number of cardiac cycles. Furthermore, recent developments in telecommunication and information technology have enabled expert-based health care to be provided at home, and a reliable ECG analyzer is also an essential component of such system [3]~[5].

A widely used ECG analyzer is a beat-to-beat analyzer that detects the QRS complex in the ECG and diagnoses rhythm irregularity [6]. One cardiac cycle is determined by detection of a point in the ECG that falls between onset and the end of the QRS complex. The durations of two QRS complexes are measured for rhythm analysis. Nine algorithms for detection of QRS complexes are widely used. Friesen et al. evaluated the noise sensitivities of these nine algorithms for detecting QRS complexes [7]. They concluded that an algorithm using a digital filter had the best performance for composite noise. It could be concluded that the algorithms used for detecting QRS complexes are sufficiently reliable for rhythm analysis.

An ECG analyzer is also used to diagnose an ischemia episode and myocardial infarction [8]~[13]. To diagnose ischemia, the ST-segment, which is a part of the ECG from the J point to onset of the T wave, must be detected. To detect an ST-segment, the S point must first be detected and then the J point, which is the inflection point following the S point, must be detected. Stamkopoulos et al. pointed out the following problems in detection of the ST segment: slow baseline drift, noise, sloped ST change, patient-dependent abnormal ST depression level, and varying ST-T patterns in an ECG of the same patient. A number of methods have been proposed to detect the ST-segment [10][14]. Stamkopoulos et al., using 34 files of the European ST-T database [10], found that overall classification indexes are 79.32% for normal beats and 75.19% for abnormal beats. More effort is needed to improve the classification indexes.

As mentioned above, the reliability of an ECG analyzer depends on how precisely it can detect the characteristic points (CPs), i.e., onset and/or offset of the waves and complexes constituting the ECG. There are two main problems that make detection of CPs difficult: 1) noises contaminating the ECG and 2) individual variation of waves and complexes in the ECG. Typical noises that contaminate an ECG are power line interference, electrode contact noise, motion artifacts, muscle contraction, and baseline drift and ECG amplitude modulation with respiration [10]. Since the pattern of waves and complexes are patient-dependent, they are slightly different for each individual. Moreover, patterns in the ECG change according to patient's body condition. In this sense, it is difficult to determine template patterns to recognize waves and complexes. To develop a reliable analyzer, a method that overcomes these two problems must be found.

The QRS wave is the most remarkable pattern in the ECG, as shown in Fig. 1, and is therefore used as a ref-

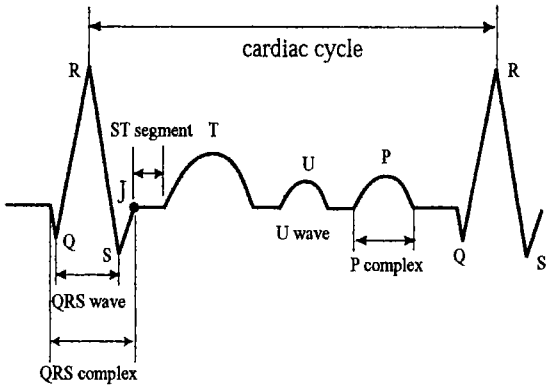

Fig. 1. A cardiac cycle of an ECG that consists of waves and complexes. The complexes and waves are extracted by detecting CPs. A part of the ECG from the Q point to the S point is called as a QRS wave in this paper.

erence pattern for detecting other waves and complexes. We call a part of the ECG from the Q point to the S point a QRS wave in this paper. Thus, the establishment of a method for accurate detection of the QRS wave would be a starting point in the development of a reliable ECG analyzer. Furthermore, the QRS wave provides useful information for diagnosis of heart diseases. This wave is detected by detecting two CPs, the Q and the S points.

One widely used method for detecting these CP is based on first and second derivatives of the ECG in the search region, which are determined on the basis of prior physiological knowledge [15]. The method could not be robust to noise. Another popular method is the syntactic method [16]. In this method, the ECG is divided into primitives, which are waves, complexes, and segments. This method is reliable if the primitives of the ECG do not change greatly from the primitives that are prepared in advance. Recently, Wavelet transform (WT) has been used to detect CPs [17]~[20]. This is a powerful method for detecting CPs, but a large amount of computation is needed for convolution of the input signal with a modulated pulsation to provide a time-frequency distribution. Therefore, this method cannot be used for real-time monitoring in coronary care unit.

We have developed two methods for detecting two CPs, i.e., the Q and S points. One method is based on a neural network (NN) of ART2 [21] [22]. ART2 has capabilities that are learning and self-organization to newly input patterns. The template patterns stored in the NN are modified in response to new input patterns, and pattern recognition is carried out using these modified template patterns. The method overcomes pattern variation of the ECG. The other method is based on dynamic programming (DP) matching [23]. DP matching is a robust pattern recognition method and overcomes the problem of noise contamination in an ECG.

In this paper, we present a method for detecting two CPs, the Q and S points, in order to extract the QRS wave. This method overcomes the current problems in detection of CPs: DP-matching is used to overcome the problem of noises contamination, and a neural network of ART2 is used to overcome the problem of individual pattern variation. These two methods are fused using a multichannel ART-based neural network (MART). The paper is organized as follows. In the next section, a preprocessor used to extract the QRS wave is described. The method for detecting the CPs using ART2 is described in section 3. In section 4, detection of CPs with DP matching is described. Fusion of the two methods, ART2 and DP matching, using MART is described in section 5. The result of evaluation of the present method using an MIT/BIH arrhythmia database are presented in section 6. Finally, conclusions are presented in section 7.

2. Preprocessor

We used ECGs in an MIT/BIH arrhythmia database for this study. The ECGs have been digitized at a rate of 360 Hz, a sampling rate that is not sufficient for precise detection of CPs. We therefore transformed the ECGs into analog signals using *Fourier* and inverse *Fourier* transforms and then sampled them at a rate of 500 Hz. This was performed using *MATLAB*. An ECG must be divided into cardiac cycles to detect CPs. Division into cardiac cycles is performed by detection of the R point. The R point is detected using an algorithm proposed by Hamilton and Tompkins [24]. In this algorithm, high- and low-frequency components that are not components of the QRS are removed with low-pass and high-pass filters. After elimination of low- and high-frequency components, the algorithm enhances the QRS complex and suppresses other parts of the ECG using differentiation and squaring filters. Then time averaging is carried out by adding the 32 most-recent values of the ECG from the squaring filter. The R point is located by detecting the location of the largest peak of the time-averaged ECG.

3. Detection of CPs with ART2

In this section, we describe pattern recognition with ART2 and the method for detecting CPs using ART2.

3.1 Pattern recognition with ART2 Carpenter and Grossberg proposed the ART2 neural network for self-organizing pattern recognition with stable presentation of stored patterns [25]. The ART2 neural network consists of an attentional subsystem and an orienting subsystem. As shown in Fig. 2, the attentional subsystem consists of an F1 layer of a feature detector, an F2 layer of a category representation, and bottom-up and top-down long-term memories (LTMs). Each node in the F1 layer is connected to all nodes in the F2 layer, and all nodes in the F2 layer are also connected to each node in the F1 layer. The connections from all nodes in the F1 layer to one node in the F2 layer form the bottom-up LTM. The bottom-up LTM is also called an instar. Conversely, the connections from one node in the F2 layer to all nodes in the F1 layer form the top-down LTM, which is called a outstar.

ART2 recognizes input patterns through the hypoth-

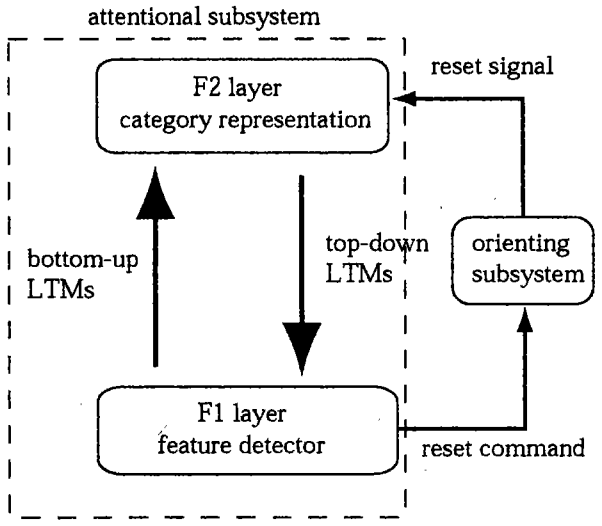

Fig. 2. An architecture of ART2.

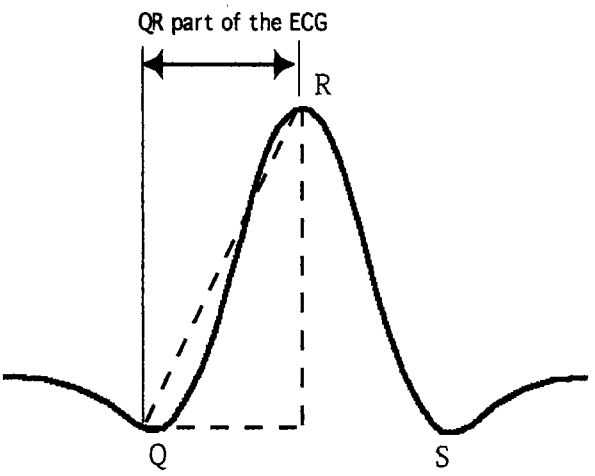

Fig. 3. Principle of detection of CPs using ART2.

esis testing cycle as follows. When a pattern is inputted into the F1 layer and the activity of the node in the F1 layer is sufficiently large, the node generates an excitatory signal along the bottom-up LTM to the node in the F2 layer. The signal is multiplied by the bottom-up LTMs. Each nodes in the F2 layer receives the signal and is activated in proportion to amplitude of it. Since the F2 layer is a competitive network, each node sends an inhibitory signal to all other nodes in the F2 layer. Then only one node is chosen a winner through this competitive interaction among nodes. The winner node associates a pattern to the F1 layer through the top-down LTM. In the F1 layer, the associated pattern is compared with the input pattern, and if the difference between the two patterns is larger than the predetermined threshold, the F1 layer sends a reset command to the orienting subsystem. The orienting subsystem then sends a reset pulse to the winner node so that it is strongly inhibited and cannot be activated again until the hypothesis testing cycle ends. After that, input pattern is reinstated and generates an output pattern to the F2 layer, again. The hypothesis testing cycle ends when the top-down LTM associates a pattern that approximately matches the input pattern. After pattern recognition, the bottom-up and top-down LTMs, which are linked to the winner node in the F2 layer, learn new information about the input pattern. In other words, weights can be modified by the input pattern.

3.2 Detection of CPs To detect the CPs using ART2, we assume that the part of the ECG from the R point to the Q point or to the S point can be approximated by a right-angled triangle as shown in Fig. 3. Fifty right-angled triangle patterns are stored in both the bottom-up and top-down LTMs. The lengths of the bases of the triangles are different. These triangles are used as the initial values for pattern recognition. For Q point detection, the part of the ECG 100 ms in length from the R point towards the P wave (the QR part) is inputted into the F1 layer of ART2. ART2 recalls the right-angled triangle that is closest to the input pattern from the top-down LTMs. If the recalled pattern is sufficiently similar, ART2 recognizes this recalled pattern as the input pattern. Then the left end of the triangle locates the Q point. The S point is also located in the same manner.

4. DP Matching for Detection of CPs

Dynamic programming (DP) was originally proposed by Bellmann to provide an efficient mechanism for sequential decision-making. DP matching is a robust pattern recognition method and is widely used in engineering problems. The algorithm of DP matching is based on the principle of optimality [26]. DP matching is a technique of pattern matching. In DP matching the distance between patterns is computed using the principle of optimality. We prepare template patterns that are compared with reference pattern by the algorithm of DP matching. The template pattern with the smallest distance to the reference pattern is chosen. For detection of CPs, we prepared two template patterns, shown in Fig. 4, which have been empirically established by observing a large number of QRS waves [27]. The QR part is used to detect the Q point. Since the ECG is digitized at a rate of 500 Hz, there are 50 ECG samples in the QR part.

The template and reference pattern are each represented by a time series. The distance is computed by these time series according to the principle of optimality. In the process of DP matching, the template patterns are stretched and/or shrunk by the algorithm of DP matching.

The distance between the template pattern (a) and the QR part is computed using the DP matching algorithm. The distance between the template pattern (b) and the QR part is also computed. The template pattern showing the smaller distance is employed to detect the Q point.

The template pattern chosen is stretched and/or shrunk by the algorithm of DP matching, which is represented by $\tilde{QR}$. The Q point is detected in $\tilde{QR}$ using

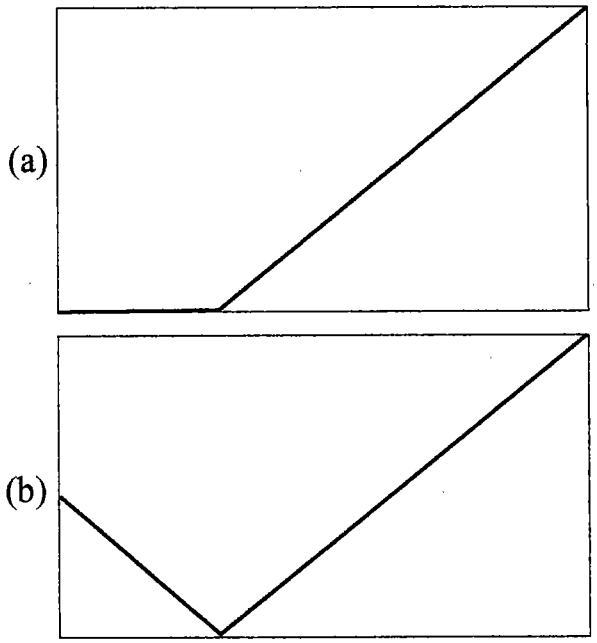

Fig. 4. Template patters for detection of CPs by DP matching.

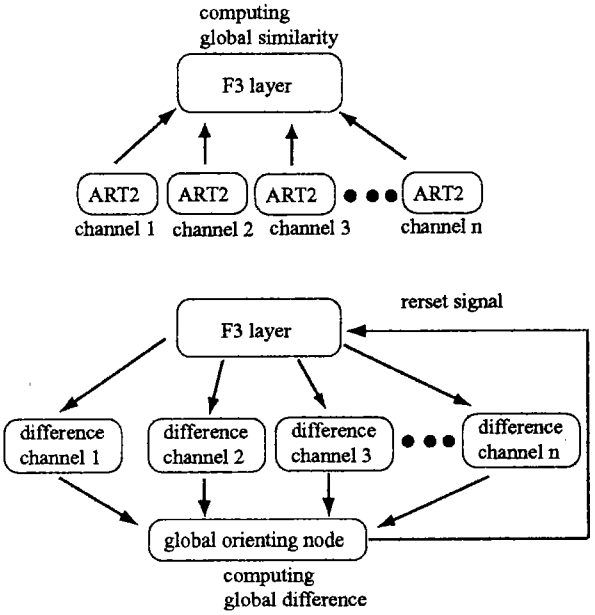

Fig. 5. Basic architecture of MART. The upper and lower panels show upward and downward flows of information, respectively.

a slope detection technique. This is found heuristically through trial and error. An established region is determined to locate the Q point. A sample $\tilde{QR}(s)$ is chosen in the $\tilde{QR}$ part. The established region is from $\tilde{QR}(s)$ to $\tilde{QR}(s+10)$. We compute $\Delta = \tilde{QR}(s+n+1) - \tilde{QR}(s+n)$ for $(n = 1, 2, ..., 10)$. If the number of $\Delta \geq 0$ is greater than or equal to seven, $\tilde{QR}(s)$ is detected as the Q point. The first $\tilde{QR}(s)$ is set at the left end of $\tilde{QR}(s)$. $\tilde{QR}(s)$ is tested to find the Q point in the direction towards the R point, and once the $\tilde{QR}(s)$ satisfying the above condition is found, the $\tilde{QR}(s)$ is located as the Q point. The S point is also located in the same manner.

5. Fusion of ART2 and DP matching methods by MART

As mentioned in section 1, two problems must be overcome for reliable detection of CPs. The first problem is individual pattern variation in the ECG and the second problem is noises contaminating the ECG. The learning and self-organizing abilities of ART2 overcome the first problem, and DP matching overcomes the second problem. These two methods are therefore fused to reliably detect the CPs using MART.

5.1 MART MART is a multichannel neural network [28]. The each channel of MART is ART2. The basic architecture of MART is divided into two parts, upward and downward flows of information, as shown in Fig. 5. In the upward flow of information, a set of patterns is inputted into the corresponding channel of ART2. Information from the activated nodes in the F2 layers of ART2 of the each channel are sent to the F3 layer of MART. Competitive interaction among the nodes in F3 layer results in activation of only one winner node, and the other nodes are inhibited to be inactive. The winner node represents a global similarity to classify the set of input patterns to a specific category.

In the downward flow of information, the winner node activated by the upward flow of information associates a set of template patterns to corresponding difference channels. The distance d between the set of input and associated patterns is computed in the global orienting nodes. This is a global difference. When d is smaller than a global vigilance parameter ρ_g, the current set of input patterns are assigned to the category. Then, if d is also smaller than a similar criterion, ρ_a, the set of template patterns is modified by the set of input patterns according to the learning equation of MART. Moreover, if d is larger than ρ_g, a reset signal is sent to the F3 layer, and the activated node is inhibited and a new pattern recognition cycle begins. The cycle is repeated until either a category is found for which d is smaller than ρ_g or the set of current patterns is assigned to a new category.

5.2 Fusion of ART2 and DP matching methods to detect CPs MART with two channels is used to fuse ART2 and DP matching methods. Two patterns are prepared for Q point detection. One is the QR pattern in the ECG. It is inputted into channel one of MART. There are 50 right-angled triangles stored in both bottom-up and top-down LTMs of ART2 of channel one of MART as template patterns. The lengths of the bases of the triangles are different and the heights of the triangles are 1.0. The QR pattern is then filtered by the bottom-up LTMs and activates nodes in the F2 layer. Each node in the F2 layer is activated in proportion to the similarity between the input ECG and the right-angled triangle patterns. Each node in the F2 layer sends a signal to the F3 layer of MART. The strength of the signal is in proportion to the activation

level of each F2 node.

The other pattern is prepared as follows. From the QR pattern, the Q point is detected using the algorithm based on DP matching described in section 4. A rectangle is made using that Q point that is detected by DP matching. The base of the rectangle extends from the R point to the Q point. This rectangle is inputted into channel two of MART. There are 50 rectangles stored in both the bottom-up and top-down LTMs of ART2 of channel two as template patterns. The lengths of the bases of the rectangles are different, and the heights of the rectangles are 1.0. The nodes in the F1 layer of ART2 receive the rectangle pattern, and each node is activated in proportion to the input signal. Each node sends a signal to nodes in the F2 layer through bottom-up LTMs, and then the nodes in the F2 layer also send signals to the F3 layer of MART. In this manner, nodes in the F3 layer receive signals from both channel one and channel two, so that the two methods, ART2 and DP matching, are fused by MART.

CPs detection in MART is performed as follows. In the F3 layer, the signals from both F2 layer of the channel one and two are fused to compute the global similarity for the set of input patterns. The activated node associates right-angled triangle pattern to the difference channel one and it also associates a rectangle to the difference channel two. Then each associated pattern is compared with each corresponding input pattern, and the difference is summed to compute d.

$$d = x_1 d_1 + x_2 d_2, \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \quad (1)$$

where x_1, x_2 are the credibility of channels and d_1, d_2 are the difference between the input pattern and the template pattern for the winning category in channel one and channel two, respectively. If d is smaller than ρ_g, the winner node in the F3 layer classifies the set of these patterns to a specific category. At that time, the left end of the associated rectangle locates the Q point. On the other hand, if d is larger than ρ_g, a reset signal is sent to F3 layer and the process continued until a match is found or all the selected categories exhausted. In this case, the input ECG is largely different from the previously input ECG by irregular rhythm and/or measuring error. This ECG is classified into different category as an abnormal ECG. By this classification, we can monitor the abnormal ECGs. The S point is also detected in the same manner. After the CPs have been detected, stored patterns in the LTMs of ART2 of channel one z_{jk^*} are updated by the learning equation of MART, when $d < \rho_g$ and $d_1 < \rho_a$.

$$z_{jk^*}(n+1) = \frac{[A_z z_{jk^*}(n) + A_1 I_j(n)] - m_{k^*}}{M_{k^*} - m_{k^*}} \quad (2)$$
$$(j = 1, 2, ..., 50;\ k = 1, 2, ..., 50)$$

$$m_{k^*} = \min_l [A_z z_{lk^*}(n) + A_1 I_l(n)] \quad (3)$$

$$M_{k^*} = \max_l [A_z z_{lk^*}(n) + A_1 I_l(n)] \quad \cdots\cdots \quad (4)$$
$$(l = 1, 2, ..., 50).$$

In (2), k^* is the index of the winner node in the F3 layer, $I_j(n)$ is the input signal to the jth node in the F1 layer, and A_z and A_1 are parameters of MART. The parameters are $\rho_g = 0.37$, $\rho_a = 0.1$, $A_1 = 0.25$, $A_z = 0.75$, $x_1 = 0.8$, and $x_2 = 0.2$.

6. Results and Discussion

The reliability of an ECG analyzer depends on how precisely it can detect the characteristic points. The QRS wave is the most remarkable pattern in the ECG and is therefore used as a reference pattern for detection of the other waves and complexes. Thus, accurate detection of the QRS wave is a starting point in the development of a reliable ECG analyzer. There two main problems that make detection of these CPs difficult: 1) noises contaminating the ECG and 2) individual variation of waves and complexes in the ECG. We proposed a method to overcome these problems. DP matching is used for overcoming the problem of noise contamination, and a neural network of ART2 is used for overcoming the problem of individual pattern variation. These two methods are fused by MART.

The reliability of the present method for detection of CPs in an ECG was tested using ECGs stored in an MIT/BIH arrhythmia database. For precise evaluation, we chose ECG record numbers in which CPs can be visually located clearly. The record numbers of the ECGs used were 100, 103, 112, 113, 115, 117, 122, 123, and 124. A total of 1,800 cardiac cycles of the ECGs were used for evaluation. For the evaluation, the Q point is defined as the first inflection point in the part of the ECG from the R point towards the P point [15]. The S point is also defined as the first inflection point in the part of the ECG from the R point toward the T point. However, since the ECG is contaminated by noises, these definitions might not be effective for the ECG in practical measurement. To evaluate detected CPs correctly, a part of the ECG including the QRS wave was expanded and drawn on a display of a personal computer. A referee found the locations of the Q and S points visually. This was carried out by examining the slope change of the ECG and the wave form of the ECG before and after the visually found Q and S points. An example of detection of the CPs is shown in Fig. 6.

The detection error was computed as

$$S_{error} = |n_c - n_v|, \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \quad (5)$$

where n_c is the point on the ECG where a CP was detected using our method, and n_v is the point on the ECG where a CP was located by the referee. Fig. 7 shows a summary of the results of evaluation. The rates of accuracy with $S_{error} \leq 6.0\ ms$ were 99.6% for S point detection and 96.4% for Q point detection. Table I shows the standard deviations (SDs) between detected CPs and CPs visually located, in which the results of detection of CPs by the present method are compared with those using DP matching and ART2. The SDs of the present method are lower than those for detection of both Q and S points.

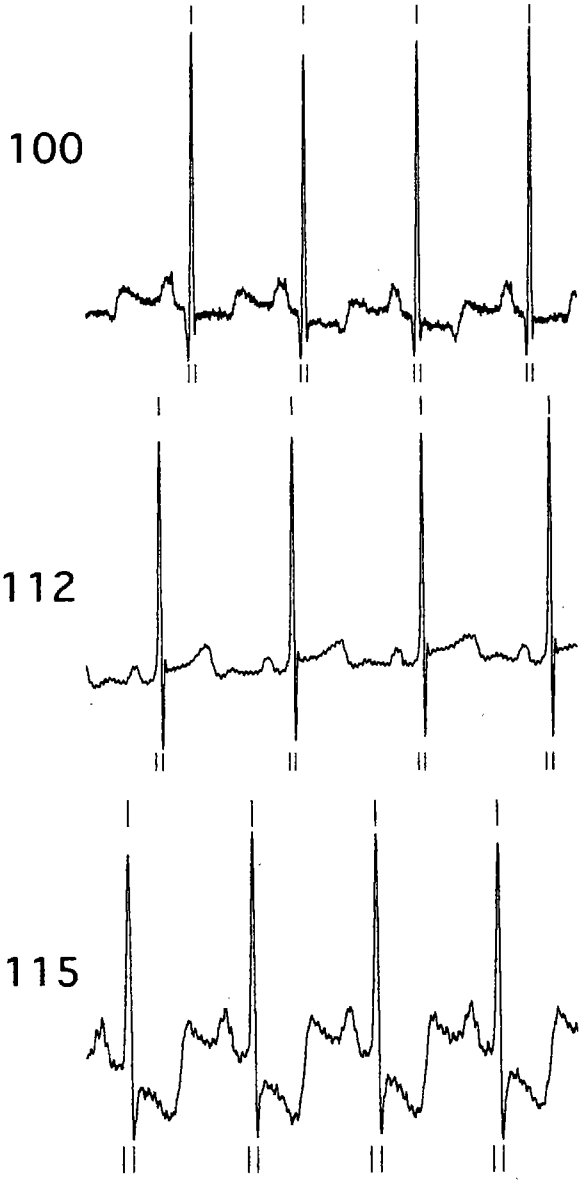

Fig. 6. Example of the CPs detection. Vertical solid lines indicate detected CPs.

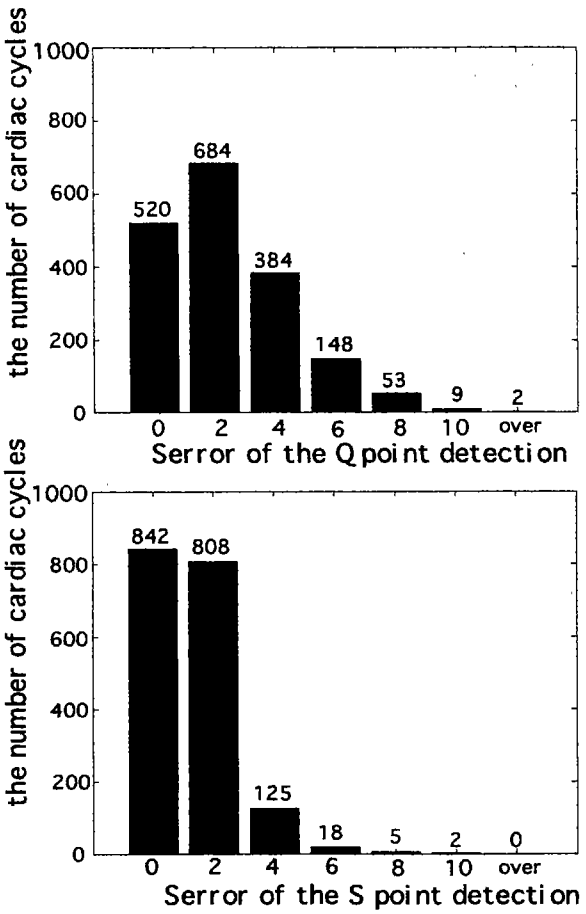

Fig. 7. Summary of results on detection of CPs.

The limit of SDs determined by the CSE committee for detection of the onset of a Q wave and the end of a QRS complex are 6.5 and 11.6, respectively [29]. These limits were determined by data obtained from the CSE ECG library, which are different from ECG obtained from the MIT/BIH arrhythmia database. The Q point, S point, the onset of a Q wave, the end of a QRS complexes are characteristic points of a QRS complex as in Fig. 1. Furthermore, ECGs in the MIT/BIH database are abnormal, which could provide severe condition for the evaluation. Therefore, it can be consider that SDs determined by CSE committee could be an index to evaluate the present method. As shown in Table I, the SDs of Q and S points detection by our method are 3.2 and 1.8, respectively, which are within the limits. These results show that the present method has good potential for detection of CPs on an ECG.

Table 1. Standard deviations of S_{error}.

SD	Q point	S point
Present method	3.2	1.8
ART	3.8	2.9
DP matching	4.9	2.4

7. Conclusion

We proposed a new method to detect the CPs, the Q and S points, in ECG by fusion of DP matching and NN. The methods overcomes two problems to detect CPs: 1) noise contamination, and 2) individual variation of waves and complexes in the ECG. Experimental results showed that the present method has good potential for the detection of CPs.

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