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An Approach to Detect QRS Complex Using Backpropagation Neural Network

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Abstract: - Backpropagation Neural Network is used to learn the characteristics of R peak to detect QRS complex. This allows R peak to be differentiated from large peaked T and P waves with higher accuracy and minimizes the problem associated with the noises in the ECG signal includes power line interference, motion artifacts, baseline drift, ECG amplitude modulation and other composite noises. The features that trains the network includes amplitude, differentiation value, duration exceed threshold, RR interval and crossing-zero. The performance was tested and resulting in accuracy to detect the correct positive peak was 91.16%.

Key-Words: - Backpropagation, QRS Complex, ECG Signal

1 Introduction

The ECE signal contains diagnostic information and for this reason is routinely used in clinical practice [1]. In order to reach the information in an ECG signal its QRS complexes must be detected. If these points can be detected accurately then the heart rate can be calculated. Recently Neural Network (NN) based methods have become popular in finding the fiducially points of these signals [2, 3].

The early algorithm to detect QRS complex is done by Digital Signal Processing. Bandpass filter is used to filter out noise and low frequency signals. This is because QRS complex usually has the highest amplitude and the highest frequency. However, ECG signals for each individual, and under different situations like exercising, sleeping, exciting, etc, are different. The choosing of the cutoff frequency and bandwidth creates difficulties due to the variety of ECG signals of different individuals [4]. Neural network can help to solve this problem. This is because neural network is adaptive to the nonlinear and time-varying features of ECG signal. It can be trained to recognize the normal waveform and filter out the unnecessary artifacts.

Discrete wavelet transform and wavelet filtering are useful in detection of noisy ECG signal. It gives good results for data including wide T waves. However, if the size of the window is very large, the detection of QRS duration increases and if the size is small, the detecting QRS numbers decrease [5]. Neural Network does not have problem of choosing window size of moving average system like wavelet transform. Neural Network learns adaptively.

Hilbert Transform finds peak by zero-crossing point in its first differential waveform d/dt [6]. P and T waves are minimized in relation to the relative peak corresponding to the peak of QRS complex in Hilbert sequence. Neural Network is better because Hilbert Transform involves complex equation calculations. Besides, looking at zero crossing point alone is not enough in determining QRS complex. P, QRS complex and T waves can have similar differential values. Neural Network can consider more parameters besides zero-crossing point.

Other Detection Methods Using Neural Network, such as Self-organizing map can be used to classify P, Q, R. S, and T portions of ECG signal. However, initially it needs an extra preprocessor to detect R point accurately [7]. However, R point is the most essential point to detect. It is mostly used for points classification after R point is detected correctly. Backpropagation Neural Network can do feature extraction directly from the signal.

Auto-associative Multilayer Feedforward Neural Network is a template matching method [8]. All the possible normal ECG signals are fed into the network so that it can learn to recognize normal ECG. When ECG signals corrupted with noise are fed in as input, the network will try to reconstruct the most similar waveform without noise from its memory (template matching). It is simple and cost-effective to run on hardware. It is used for signal reconstruction but not QRS complex detection.

Adaptive resonance theory is good for classification. When a pattern is recognized, "resonance" occurs [9]. If there is no pattern associated, new class is created. However, compared with Backpropagation, it is more Complex and difficult to design. It can lead to instability easily if the design is not comprehensive enough.

ECG signals may be corrupted by various kinds of noise. The noise types include electromyography interference, 60Hz power line interference, and baseline drift due to respiration, abrupt baseline shift, and a composite noise constructed from all of the other noise types.

Backpropagation has a better prospect for the QRS detection. It is the most straightforward and comprehensive method as it has a set of defined algorithms and rules for training.

In this paper, a robust algorithm for QRS detection using backpropagation is proposed. The network considered the existence of noises in the ECG signal, including Power Line Interference, Motion artifacts, Baseline drift, ECG amplitude modulation with respiration and other composite noises [10].

2 Design Methodology

The network designed with 6 inputs, which are amplitude, differentiation, duration, RR interval, zero-crossing flag and first-element flag for each point that needs to be judged if it is an R peak. The network is trained to output 1 for R peak and 0 to non-R peak.

There are 13 neurons in the hidden layer. There is no definite way of determining the right number of neurons in hidden layer. It is chosen based on Kolmogorov's theorem [11]. Kolmogorov's theorem states that if the number of input neuron is m, and the inputs are scaled to lie in the region from 0 to 1, a network with only one hidden layer and 2m+1 neurons in this layer can exactly map these inputs to the outputs. There should not be any constraint on the output for this theorem to be applicable. Therefore, 6*2+1 = 13 neurons are chosen as the number of neurons. However, Kolmogorov's theorem does not specify whether this network is an optimum solution for this mapping. The network with this number of neuron in hidden layer may not be the simplest to do the mapping. However, due to the cause that with 13 neurons, the network still takes quite some time for training, the number is not reduced for optimized solution.

The decision of choosing number of neurons in hidden layer actually still remains a challenge. If the number of neuron is too large, the network needs more storage and the training is more complicated. The memory is distributed over large number of weights. Some weights may be insignificant to the overall performance. But if the number is too small, though the network still can do the exact mapping, there maybe over fitting. Over fitting means that the network cannot make generalization when presented with slightly different inputs.

The network is initialized with the following settings:

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net.trainParam.show = 100;
net.trainParam.epochs = 800;
net.trainParam.goal = 1e-3;
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It means that for every 100 iteration, the error is displayed once. The maximum epoch for training is 800 and the goal is to reach error at 1e-3. For each training session, the training stops when either reaches maximum epochs or goal error.

The network is trained with 20 signals. The total points fed into the network are around 1000 input-target pairs. The signals are with different amplitudes, heart rate, and noise level.

The weight and bias values are saved for each training session. When the simulations are not satisfactory, the network is trained one more time with the last saved weight and bias values. This can improve the network and reduce the number of time of training.

Preprocessing and post processing are used before and after training. This is because the range of values for different parameters differs too much. For example, RR interval is normally below 350, but amplitude can be as large as 30000. Preprocessing normalize the inputs so that training becomes smoother and faster. The output is post processed to get back to original range.

2.1 Flow of Algorithm

In the case of QRS complex detection, the network is trained to memorize the characteristics of an R peak. One of the distinct features of R peak is large amplitude compared with other portions of ECG like P and T waves. R peak has high differentiation value due to sudden large amplitude change over short period.

Besides, the duration of QRS complex exceeding certain threshold is usually large than the other parts of signal. R peak is also a maximum point with high positive threshold at QR portion and high negative threshold at RS portion. If we plot the differentiation signal, there is crossing zero point from positive to negative. Besides, usually the interval between RR is almost constant for a particular ECG signal.

If the point is the first point exceeding in a signal, first-element flag is set. This is to let the network learns that the first element can have variable RR interval, since the RR interval calculated is the distance from zero point.

These attributes, amplitude, differentiation, duration, approximate RR interval, and zero-crossing flag, first-element flag are used to train the network to recognize R peak.

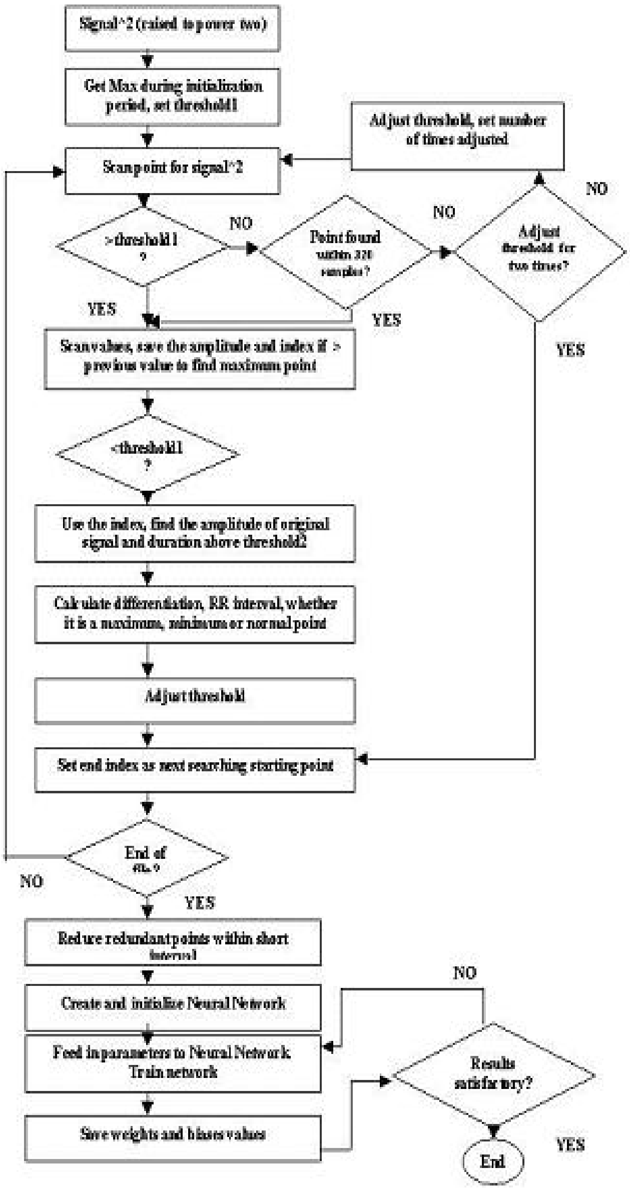

Fig. 1: Flow Chart of QRS Complex Detection Algorithm

2.2 Flow Chart

The flow chart of QRS complex detection is shown in Fig. 1. The signal is amplified by power two to amplify the signal with large amplitude and reduce the effects of high frequency but low amplitude noise. This is also to detect peaks that have low axis due to base line drift. When the signal is amplified by power two, the negative peak with high amplitude can be detected when the positive is low.

The threshold has adaptive nature. The maximum is chosen over an initialization period. The maximum is recalculated when a peak is found to reflect the effect of the current peak. If the peak is low, the threshold is lowered for the next peak, and vise versa. This is to deal with base line drift effect. The threshold is lowered when a possible peak is not detected over a maximum period. The search is rechecked over the period in case the peak suddenly goes low due to noise and base line drift. The adjustment of the formula is as followed:

threshold1 = 0.3875*Xmax;
threshold2 = sqrt(threshold1);
threshold3 = -threshold2;

When a value greater than the threshold is found, it scans the maximum for the duration the values greater than the peak. Then the next peak is found from the end of the duration. For every possible peak found, the differentiation and the original amplitude at that point is calculated. There is a second threshold for the original peak. The duration of the original signal is found.

Since the R peak always has the highest frequency, the differentiation is found. If the current differentiation value is positive and the next value is negative, a crossing-zero flag is set to one to indicate it is a maximum value. If on the other hand, the current differentiation value is negative and the next is positive value, the crossing-zero flag is set to negative to indicate that this is a minimum point.

The interval between the current point and the previous possible peak is calculated. This is to get the approximate RR interval to determine if the point is an R peak.

The parameters of amplitude of original signal, duration over second threshold, differentiation value, possible RR-Interval and crossing -zero point are written to a file.

Then the file is re-opened to check if there are any points that are redundant. A minimum RR-interval is chosen as 5 points. Since the signal is encoded as 128 samples per second and the normal human heart beat are 72 per minute. It is equivalent to 1.2 beats per second. Then the average RR interval is around 128 points for one QRS complex to detect. The RR low is set to 5. It is very unlike that two QRS complexes occur within 5 samples. So for peaks that are less than 5 samples from the previous possible peak, the peak with highest amplitude is chosen and the remained are discarded.

All the remaining points are fed into the network to train the network so that it can remember the characteristics of an R peak. During simulation, data that have characteristics close to training data will be identified as R peak.

3 Results

The network is trained with 20 signals that new to the network and tested with 10 signals. Table 1 summarizes the results of detection accuracy. A sample of training and testing signals are shown in Fig. 2 and 3 respectively.

Table 1: Results of Detection

Input signal	No. of R Peaks	No. of peaks detected	No. of missing peaks	No. of false positive	Accuracy of Detection	% of missing peaks	% of false positive
T01	7	7	0	1	100.00 %	0.00 %	12.50 %
T02	10	9	1	1	90.00 %	10.00 %	9.09 %
T03	7	7	0	1	100.00 %	0.00 %	12.50 %
T04	8	8	0	0	100.00 %	0.00 %	0.00 %
T05	7	7	0	1	100.00 %	0.00 %	12.50 %
T06	10	9	1	2	90.00 %	10.00 %	16.67 %
T07	7	7	0	0	100.00 %	0.00 %	0.00 %
T08	7	7	0	0	100.00 %	0.00 %	0.00 %
T09	11	8	3	1	72.73 %	27.27 %	8.33 %
T10	6	6	0	0	100.00 %	0.00 %	0.00%
				Average	91.16 %	8.84 %	6.51 %

Accuracy of Detection = (Number of peaks detected / Number of peaks) * 100

Percentage of Missing Peaks = (Number of missing peaks / Number of peaks) * 100

Percentage of False Positive = (Number of false positive / Total number of output peaks) * 100.

The results are considerably satisfactory, with 91.16% average accuracy. The false positive for t01, t03, t05 actually occur for the same beat. This is because there are some fluctuations for one beat. There are a few points that have high differentiation and amplitude values, with RR interval in reasonable range. Although the algorithm has reduced most of these redundant points, there may still some points are considered as R peak for one beat.

T09 has 3 peaks that are not being recognized. This is because the RR interval is relatively much smaller than average RR interval in training set. In brief, the accuracy of output depends on how many variations of signals the network is trained with. The more training sets are given to the network, the more the recognition capability of the network. The network is trained only with 20 signals.

The first results for t10 signal show that the network is capable of recognizing all of the peaks. However, this is the result of retraining the network using similar signal to t10. At the first time of testing, half of the peaks are not being recognized. This is because the intervals between peaks are relatively larger than the average RR interval in training set. However, when the network is improved and retrained by including t10 as training set, the network is capable of memorizing the output. When simulated with t10, it shows that all points are recognized.

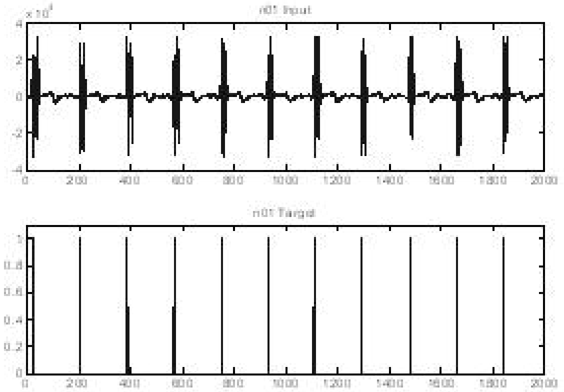

Fig. 2: A Sample of Training Signal

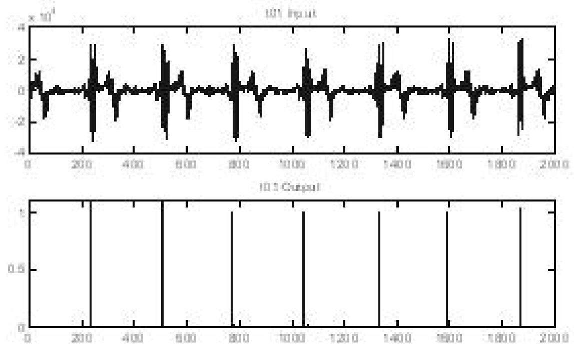

Fig. 3: A Sample of Testing Signal

4 Discussion

The threshold is checked over signal raised to power two. It is able to detect possible points even though there is baseline drift, or the positive value is distorted.

The threshold is adaptive. The threshold is adjusted every time a possible peak is found. If the peak found is large, the threshold increases, and vice versa. The threshold reflects the effects of the latest point peak found and the previous points found. The adaptive threshold is useful during baseline drift.

If multiple possible points found during a short interval, the number of possible points is reduced. It is not possible that more than one beat occur within a short interval. For example, for 128 samples per second signal, and average heart beat rate for normal human is 72 per minute, it is very unlikely that double or peaks happen during 20 samples. Therefore, the maximum point is chosen within this range. If the points are not reduced, and since all of them have high amplitude, differentiation and RR interval, they can be wrongly identified as having more than one heartbeat during that short interval.

For the first few possible peaks found, a special flag is set. This is to tell the network that for these points, the RR interval does not play significant role in the determination of whether they are R peaks. The approximate RR interval is taken as one of the parameters. However, the RR interval for the first point cannot be calculated by getting the distance from previous possible peak, therefore the flag is set.

The network is capable of learning ECG with different amplitude, differentiation value and RR interval. Its recognition capability is readily expanded if more input-target pairs are given.

For ECG signal with very high amplitude and frequency, the T wave will not wrongly be identified as R peak. This is because the interval from the previous peak is much smaller than average RR interval. For algorithm that is suggested by other researchers that does not consider RR interval, T wave may be wrongly identified.

The network is capable of making generalization from input-target files. It makes general judgment from the inputs that have been learned. When presented with signal it is not trained with, it can identify points that have close similarities from the peaks it has learned.

5 Algorithm Assessment

The network is trained with 20 ECG signals. Its performance is tested with 10 new signals. From the assessment of the results, it is found that the accuracy is considerably well, with 91.16% of correct detection, 8.84% of miss detection, and 6.51% of false detection.

The output is less satisfactory for testing signal t09 and t10. This is because both signals have relatively larger and smaller RR interval respectively compared with training set. The network does not have memories of peak detection that have RR interval that is much larger or smaller than average range of RR intervals. This finding is confirmed when testing signal t10 is used to train the network together with 20 training signals. The network is able to recognize all peaks when simulated with t10. Therefore, to improve the network performance, more peaks with more varied parameters should be used for training.

Besides, there are points that are missed out. This is because the threshold is taken over signal raised to power two values. If any point is found to exceed the threshold, it is set as the starting point for scanning for maximum point until a point becomes less than the threshold. Then the next peak searching is after the last point below threshold. Since only the maximum point is taken for evaluation, if there are positive points and negative points exceed the threshold together, the maximum point chosen may actually be a negative point. The negative point has less likely possibility to be identified as R peak, so missing detection may occur.

The point that is identified as R peak may not be exactly be the very actual R peak. This is because there are multiple points when a QRS complex occurs. This is due to noise and interference. The amplitude, differentiation and RR interval from previous peak for these points are very close. Usually, the network takes first point from this group of possible peaks.

The algorithm is suitable for normal ECG. It is not suitable for ECG with heart abnormalities like atrial fibrillation. This is because the QRS complex is not distinct. It is mixed up with other waves. So the extraction of individual amplitude, differentiation, RR interval is almost impossible. There is not directly distinguishable RR interval for atrial fibrillation.

6 Conclusion

The accuracy of detecting QRS is satisfactory. If the signal is too noisy, a peak is detected when there is a heartbeat, but it may drift slightly from the actual heart beat. This happens when there are multiple relatively close high frequency and amplitude peaks detected over a small range. Noise and interference introduce this situation. Missing detection of peak seldom happens unless the peak-to-peak amplitude is really low. Detection of false positive seldom happens except during the initial period when the network tries to identify the first peak.

The network is trained by using backpropagation neural network and it can be re-train when new patterns of ECG signals are presented. The training period may take up some time, but once the network is trained, only one iteration is needed to determine QRS complex. Therefore, it is relatively fast to recognize the peaks.

It is hard to identify which are the weights that are not significant in the performance of the network. If the weights can be identified, then they can be eliminated to reduce the storage space needed.

Besides, during the training phase, it takes up large amount of time in preparing input signal to usable form, preparing target signals, training and retraining the network. Currently, we are conducting further research to overcome the above-mentioned problems.

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