NN-Based R-peak Detection in QRS Complex of ECG Signal

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Abstract — **eural Network (NN) is designed to detect QRS complex from ECG signal. QRS complex detection is essential so that RR-interval can be measured for disease classification and can also be monitoring the heart rate. In this paper, a supervised Neural Network based algorithm has been used to detect R in QRS complex. It was tried to find out the R-peak in QRS complex with missing peak and false peak as well, so that the correct decision can be made by the physician and clinician. The accuracy of finding the R-peak by using the Neural Network was 99.09% averagely and the average percentage of missing and false peak was 00.09%. The technique appears to be exceedingly robust, correctly detects R-peaks even aberrant QRS complexes in noise-corrupted ECGs.**

Keywords — **Neural Network, QRS Complex, R-peak, ECG, Heart rate.**

I. Introduction

Accurate determination of the QRS complex, in particular, accurate detection of the R-peak, is essential in computer-based ECG signal analysis especially for a correct measurement of Heart Rate (HR) and Heart Rate Variability (HRV). But this is often difficult to achieve, since various sources of existing noise contraction [1] are frequently encountered, such as baseline drifts, power line interferences, motion artifacts and, muscular activity. Several clinical applications require accurate heartbeat monitoring systems including intensive care units, operating rooms, implantable pacemakers and defibrillators. Automated algorithms detect a QRS complex when ECG amplitude exceeds a threshold level. If the threshold is too high, true beats can be missed. If the threshold is too low, false detection can result during EMG artifact and external interface [2]. Since during these artifacts the magnitude of the noise can become larger than the signal, QRS detection based on amplitude thresholding alone is not satisfactory.

To solve this problem, in this paper, the NN-based R-peak detection has been proposed. Neural Network is chosen primarily since it 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 and noises. The accuracy of R-peak detection in QRS complex can be improved by considering multiple features, including RR interval, pulse duration and amplitude.

In 1993, Bond, A.B, et al proposed band-pass filter to filter the low frequency noise of ECG signal [3]. Although, band-pass filter is simple to implement, but Neural Network is better in the sense that it does not have bandwidth selection problem like bandwidth filter. The bandwidth of the band-pass filter must be chosen to reflect the tradeoff between noise reduction and loss of high-frequency details. If the bandwidth is too large, noise reduction suffers; if the bandwidth is too low, high-frequency QRS characteristics are lost. Neural Network can learn to respond adaptively to different signals.

Kadambe, S., Murray, R., and Boudreaux-Bartels, G.F (1999) applied discrete wavelet transform and wavelet filtering for the detection of QRS complex [4]. Although, by using this method the ECG baseline is approximated and also useful in QRS detection of noisy ECG signal but, Neural Network does not have problem of choosing window size of moving average system like wavelet transform.

In 2000, Benitez, D.S., Gaydecki, P.A., and Fitzpatrick focused Hilbert Transform to find the R-peak by zero-crossing point in its first differential waveform [1]. 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. Therefore, this paper is paying attention for the accurate R-peak detection in QRS complex by using the Neural Network.

II. Interfaces and noises affecting the ECG signal

The network needs to consider the existence of noises in the ECG signal and the noise can cause inaccurate detection of QRS complex. Some of the noises are highlighted in the following sections.

Electrode Contact Noise: Electrode contact noise is transient interference caused by loss of contact between the electrode and skin, which effectively disconnects the measurement system from the subject. Electrode contact noise can be modeled as a randomly occurring rapid baseline transition, which decay exponentially to the baseline value

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and has a superimposed 60Hz component. The transition may occur only once or may rapidly occur several times in succession [5].

Motion Artifact: When motion artifact is introduced to the system, the information is skewed. Motion artifact causes irregularities in the data. There are two main sources for motion artifact, Electrode interface and Electrode cable. Motion artifact can be reduced by proper design of the electronics circuitry and set-up [5].

Inherent Noise in Electronics Equipment: All electronic equipments generate noise. This noise cannot be eliminated; using high quality electronic components can only reduce it.

Ambient Noise: Electromagnetic radiation is the source of this kind of noise. The surfaces of the human bodies are constantly inundated with electric-magnetic radiation and it is virtually impossible to avoid exposure to ambient noise on the surface of earth [5].

III. CLINICIAL IMPORTANCE OF ECG MORPHOLOGY

ECG signal is the electrical demonstration of heartbeat. The diagram below shows the components of ECG signal. ECG signal basically consists of P, Q, R, S and T waves. QRS complex that needs to be detected is the portion starting from Q point to R peak and ends at S point as shown in Fig. 1.

Heart disease is prevalent problem nowadays. Usually, it can be identified by average RR-interval, or the duration between two R peaks. Slow and accelerated heart rates are refers the bradycardia and tachycardia respectively [6]. Classification of cardiac arrhythmia to different types of abnormalities like atrial flutter, atrial fibrillation and ventricular fibrillation can be done from the heart rate. Besides, people with certain cardiac arrhythmia need to use pacemaker to keep their heart functions normally. If no QRS complex is detected within certain time range, the pulse generator is alerted to send out an artificial pacing impulse. The pacemakers may suffer noise and electromagnetic interference. If the detection of QRS is not accurate, the pacemaker may send out impulse continuously. This will shorten the lifetime of the pacemaker due to higher power dissipation. The patient may also suffer hypertrophy of the heart in long run.

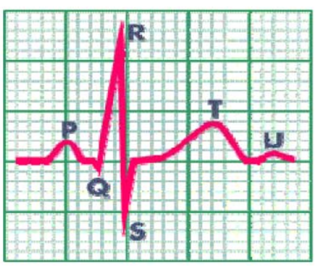

Fig. 1 QRS complex

Neural Network can help to solve this problem. This is because Neural Network can perform brilliantly with nonlinear and time-varying signals. Neural Network emulates the functions of the brain. After we present the inputs and corresponding targets to the Neural Network, algorithm can be used to adjust the weights inside the network, so as to reduce the error between the input and output. After we train the network repeatedly by using certain input signal, the next time we present certain simulation input, the network will make judgment by recalling through the weight values and give the best results.

IV. METHODOLOGY: NEURAL NETWORK

Back-propagation was created by generalizing the Widrow-Hoff learning rule to multiple-layer network and nonlinear differentiable transfer function. Widrow-Hoff learning rule is also called Delta rule, which reduces the difference between desired output and actual output. Standard back-propagation is a gradient descent algorithm. The designed Back-propagation network has two layers. It is a two-layer tan-sigmoid/linear network. Each layer has a weight matrix W, a bias vector b, and an output vector a. The architecture of the network shown in Fig. 2a and Fig. 2b, 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.

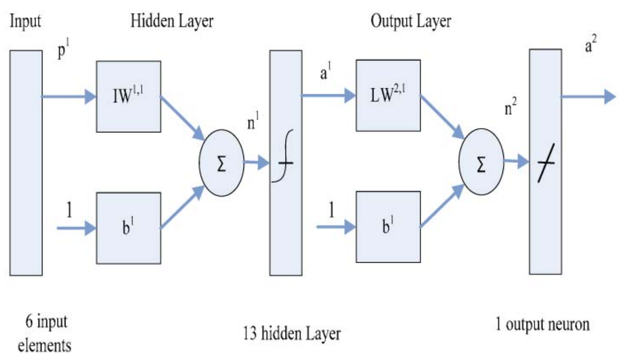

Fig. 2a Back-propagation Neural Network architecture

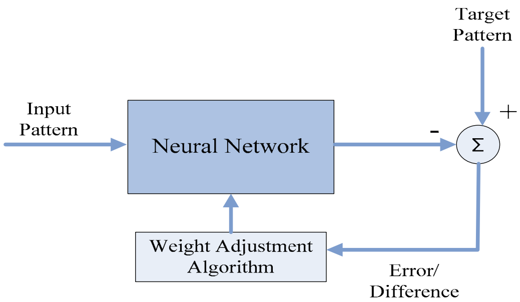

Fig. 2b Back-propagation Neural Network architecture with weight adjustment

The notation IW means input layer weight and LW means hidden layer weight. The notation $w^{a,b}_{m,n}$ means weight for the connection link between from layer *b* to layer *a*. It is the weight for *m*th neuron at layer *a* from *n*th output from layer *b*.

There are 13 neurons considered in the hidden layer. Actually, there is no specific way of determining the accurate number of neurons in hidden layer for the neural network. It is preferred based on Kolmogorov's theorem [7] 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.

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 was trained with 20 different signals. The total points fed into the network are around 1000 input-target pairs. The signals were with different amplitudes, heart rate, and noise level. The weight and bias values for both input layer and hidden layer were 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. The Preprocessing and post processing were used before and after training the network. This was 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.

V. Result and Discussion

The signals used in training and testing are downloaded from MIT/BIH PAF Prediction Challenge database website. The network was trained with 20 signals that new to the network and tested with 10 signals. Table 1 summarizes the results of detection accuracy.

Accuracy of Detection = (No. of peaks detected / No. of peaks) * 100 (1)

Percentage of Missing Peaks = (No. of missing peaks / Number of peaks) * 100 (2)

Percentage of False Positive = (No. of false positive / Total number of output peaks) * 100 (3)

According to the result shown in Table 1, it can be said that the R-peak detection algorithm is working with 99.09% average accuracy. For the testing input signal T06 only one false R peak was detected for same beat, therefore the percentages of false positive peak was very low (average 0.09%) only. This was because there are some fluctuations for one beat. There were a few points that have high differentiation and amplitude values, with RR interval in reasonable range. Although the algorithm had reduced most of

Table 1 Detection accuracy

Input signal	No. of R-Peaks	No. of peaks detected	No. of Missing peaks	No. of false positive	Accuracy of Detection
T01	7	7	0	0	100.00 %
T02	10	10	0	0	100.00 %
T03	7	7	0	0	100.00 %
T04	8	8	0	0	100.00 %
T05	7	7	0	0	100.00 %
T06	10	10	0	1	100.00 %
T07	7	7	0	0	100.00 %
T08	7	7	0	0	100.00 %
T09	11	10	1	0	90.90 %
T10	6	6	0	0	100.00 %
				Average	99.09 %

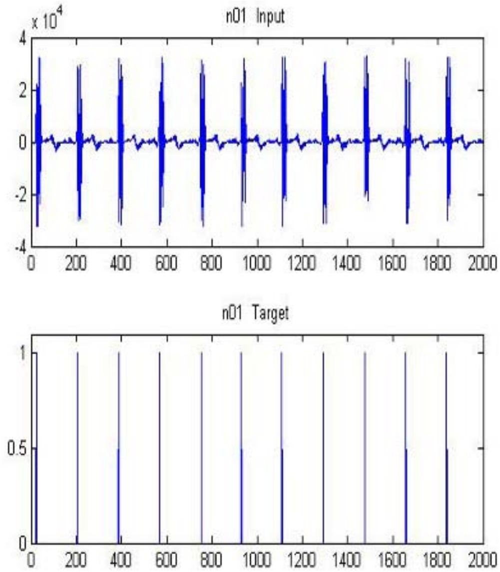

Fig. 3a Training signal for Neural Network

these redundant points, there may still some points are considered as R peak for one beat. And, for the testing signal T09, one R peak could not detect so the percentage of missing peaks was 0.09% (average) only, as because of the RR interval was relatively much smaller than average RR interval in training set. As a sample training input signal shown in Fig. 3a, as used to train the network and the network has been tested by the testing input signal shown in Fig. 3b. From the Fig. 3b, it was easily found that the network was able to detect the R peak in the QRS complex for a sample input signal perfectly. 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.

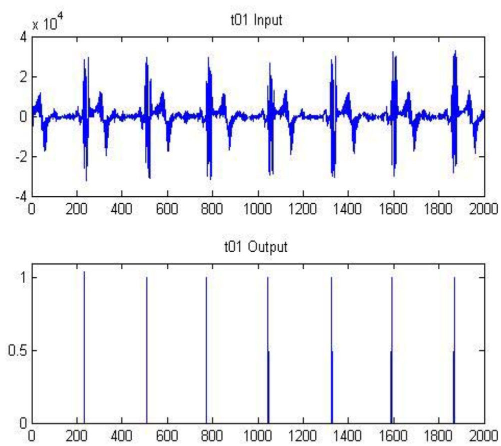

Fig. 3b Testing signal for Neural Network and output

VI. Conclusions

ECG signal contains potentially valuable information that could assist clinicians in making more appropriate and timely decisions. The ultimate reason for the interest in ECG signal analysis is in clinical diagnosis and biomedical applications. Heart Rate monitoring is a technique for obtaining important information about the condition of a person by detecting QRS in the ECG signal. Furthermore, it can be possible to know the status of the patient by measuring the heart rate. Here, the threshold is checked over signal raised to power two so that it is able to detect possible points even though there is baseline drift, or the positive value is distorted. According to the result, the accuracy of R-peak detection in QRS complex is satisfactory. 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.

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