Detection of P and T wave using Bayesian Regularisation

Nilesh Parihar, Dr. V. S. Chouhan

Abstract: The Electrocardiogram (ECG) represents the electrical activity of the heart. The ECG typically consists of the QRS, P and T waves, which provide clinical information about the functioning of the heart. It is difficult to detect P and T wave due to the overlaps and variations in amplitudes of other signals. In this paper we propose a method for Automatic Detection and classification of the P and T wave. Bayesian regularization neural network is used to learn the characteristics of P and T wave, which provides high detection rate of 94.6% for P and 91.6% for T.

INDEX TERMS: ECG, Kaiser Window, Bayesian Regularization, Levenberg- Marquardt, QRS Complex

1. Introduction:

A standard scalar electrocardiogram consists of P-wave, PR-interval, PR- segment, QRS-complex, ST-segment, ST interval and T-wave. The P-wave represents atrial depolarization, the QRS complex left ventricular depolarization and the T-wave left ventricular repolarisation [1].

To precisely measure the time between two electrical events in the ECG, it is necessary to identify parts of the waveform. The real-time detection of the P and T wave is challenging due to its relatively low amplitude, low signal to noise ratio, and the presence of the other adjacent waves. Previous works in P wave detection usually rely on digital signal processing techniques [2] even Many of these approaches delineate either P or T-waves of ECG waveforms, whereas a few approaches delineate both P and T-waves. Murthy & Niranjan used discrete Fourier transform (DFT) to delineate P and T waves, while Murthy and Prasad used discrete cosine transform (DCT). Thakor and Zhu used adaptive filters for delineation of P-waves. Pietka used a combination of syntactic methods and methods based on measurement vectors by applying the attribute grammars. Trahanias and Skordalakis used attribute grammar for the detection of P and T-waves [3].

For detection of P- and T-waves: For the detection of P- and T-waves should be capable of appreciating the low slope and low magnitude of the wave components, as contrasted to QRS-complexes containing peaky waves with prominent slope and magnitude.

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Further, to ensure sufficient magnitude of the extracted feature, so as to meet the thresholding needs; the proposed algorithm is to detect the components of P and T wave. The detection of P- and T-waves is done with the reference of QRS on and off time, in that it search intervals for P and T -waves between each successive pair of QRS off time and the subsequent QRS-on time[5].

2. Methodology

Neural networks have been trained to perform complex functions in various fields like pattern recognition, identification, classification, speech and extras. In that once the network weights and biases are initialized, the network is ready for training with proper network inputs p and target outputs t.

In automated bayesian regularization, it is desirable to determine the optimal regularization parameters in an automated fashion. In this approach overcome the over-fitting problems with early stopping and Bayesian Regularization.

Early stop approach is the process in which the data set is divided into three subsets: training, test, and verification sets. The test set is used to test the trend of the prediction accuracy of the model trained at some stages of the training process. At much later stages of training process, the prediction accuracy of the model may start to get worse for the test set. This is the stage when the model should cease to be trained to overcome the over-fitting problem[6,7].The Bayesian Regularization approach involves modifying the usually used objective function, such as the mean sum of squared network errors (MSE or E_d)

$$F = E_d = \frac{1}{N}\sum_{i=1}^{N}\left(e_i\right)^2$$

$$F = \beta E_d + \alpha E_w$$

Where: α and β are parameters which are to be optimized in Bayesian framework of MacKay[8,9]. It is assumed that the weights and biases of the network are random variables following Gaussian distributions and the parameters are related to the unknown variances associated with these distributions. It is a known fact that the optimal regularization technique requires quite costly computation of the Hessian matrix. To overcome this drawback, Gauss-Newton approximation to the Hessian matrix is used. The process of bayesian framework is the use of bayesian regularization function is a combination with Levenberg-Marquardt training process. Standard backpropagation is a gradient descent algorithm in which the network weights are moved along the negative of the gradient of the performance function. The trainbr algorithm generally works best when the network inputs and targets are scaled so that they fall approximately in the range [-1, 1]. If the inputs and targets do not fall in this range, we can use the function mapminmax to perform the scaling. In this the input layer consisted of nodes and in the subsequent hidden layer process neurons with the standard sigmoid activation function are used [10].

3. Algorithm for Detection

1. Load ECG database files case by case as shown in fig (a)
2. Implement FIR bandpass filter with Kaiser Window for removing of noise as shown in fig (b).
3. The output of the above step is passed through the neural network, which is having P as an input. The training function is to train neural network with bayesian regularization function having target T with a defined learning rate μ=0.05 and number of epoch=4. Further, in this step mapminmax function is used.
4. Then the output of mapminmax is trained and simulated with the input. After simulation we get the stable and desired output.
5. We apply the threshold condition to detect and mark the R–wave as shown in fig (c).
6. Now between two consecutive R-peak time intervals we will find the P wave by applying threshold condition i.e. 10% of R wave as shown in fig (d)
7. Now between two consecutive R-peak time intervals we will find the T wave by applying threshold condition i.e. 30% of R wave as shown in fig (e)

4. Graphical Results of P and T - waves

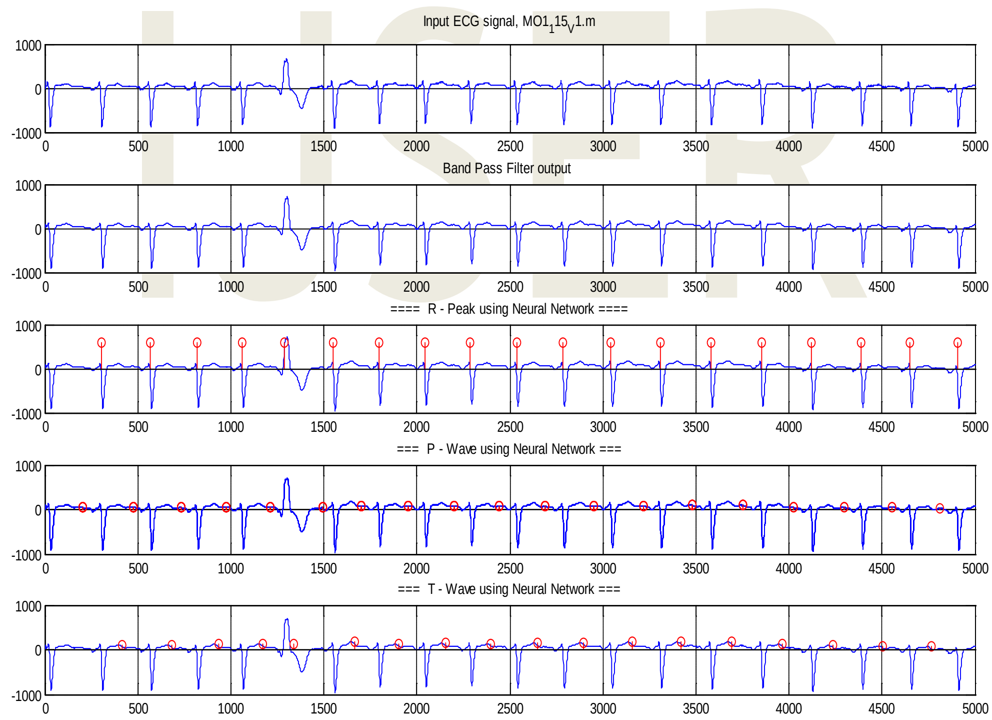

Fig: a. Input Raw CSE-ECG data, b. Filtered output, c. R peaks, d. P- wave output, e. T-wave output

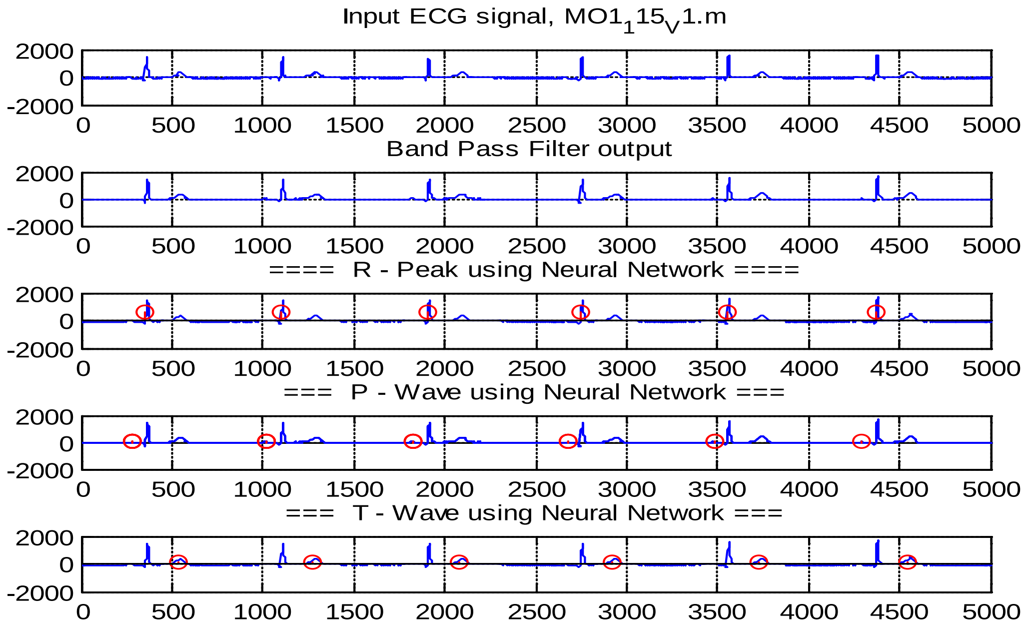

Fig: a. Input Raw CSE-ECG data, b. Filtered output, c. R peaks, d. P- wave output, e. T-wave output

5. Testing Results

In this paper Bayesian regularization neural network is used to learn the characteristics of QRS complex to detect P and T wave on the standard CSE database. Bayesian regularization gives accurate and best results. The table shows the actual number of QRS complexes (R peaks), number of P and T wave detected, true positive (TP), false negative (FN), and false positive (FP) detection for entire CSEECG library dataset-3. Each ECG record of the dataset is of 10 sec duration sampled at 500 samples per second, thus giving 5000 samples. The table also shows the detection rate (*DR*), positive predictivity (+P) and sensitivity (Se).

No. of QRS	Actual no. of P	True Positive TP	False Negative FN	False Positive FP	Detection Rate , DR	Positive Predictivity +P	Sensitivity Se
17760	16162	15291	871	40	94.6 %	94.86 %	94.61 %

Table.1. P wave Detection Results

No. of QRS	Actual no. of T	True Positive TP	False Negative FN	False Positive FP	Detection Rate DR	Positive Predictivity +P	Sensitivity Se
17760	16833	15412	1421	0927	91.6 %	92.0 %	91.6 %

Table.2. T wave Detection Results

6. Conclusion

The algorithm developed in MATLAB is implemented, with ANN based on Bayesian regularization function, for detection of P and T wave. The algorithm is rigorously tested on entire CSE-ECG dataset-3, which includes an accurate range of morphologies and vast variety of cases. The resultant values are shown in Table 1, 2 with significantly low values of FP and FN and excellent values of DR, +P and Se.

7. References

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