# Effecient ECG Signal Classification Using Sparsely Connected Radial Basis Function Neural Network

**Hafizah Husain & Lai Len Fatt**
**Department of Electrical, Electronics and Systems**
**Faculty of Engineering**
**Universiti Kebangsaan Malaysia**
**43600 UKM Bangi**

## Abstract

Precise electrocardiogram (ECG) classification to diagnose patients' heart condition is essential in getting maximum benefits via effective treatment. Artificial neural network is known to yield good results for classification of "difficult-to-diagnose" signals in medical domain. In this work, the ECG classification is performed using sparsely connected radial basis function neural network (RBFNN). Unlike the fully-connected RBFNN architecture, this type of structure reduces the computational cost and increases the classification accuracy. Only prominent features are necessary to a certain class of ECG during classification task. The ECG signal is obtained from Boston's Beth Israel Hospital. The process includes signal pre-processing, QRS complex detection, features extraction, determination of important parameter and construction of RBF network. Wavelet decomposition method was used for feature extraction process. Five features to be used are standard deviation of R-R distance, P-wave and R-wave amplitude, QS-wave distance and minimum point of T-wave. The signal is classified into three classes; normal sinus rhythm, malignant ventricular ectopy and atrial fibrillation. The results show that sensitivity value is between 75 to 100 percent while the certainty value is between 91.7 to 100 percent. In addition, this work shows that conventional RBFNN and linear discriminant analysis (LDA) produce less accurate results in terms of overall classification accuracy.

**Keywords**: ECG signal; Radial basis function neural network; sparsely connected; wavelet decomposition; classification problem

## 1. Introduction

ANN has a significant advantage to solve problems that either do not have an algorithmic solution or solution that is too complex. These networks have been applied effectively within medical domain for clinical diagnosis (Lip, 2001), image and signal analysis and interpretation of these signals (Silipo, 1996). The conventional RBFNN has been identified as one of the ANN structures that can accurately perform classification tasks. This network is a nonlinear, multidimensional function mapping which has built into a distance criterion with respect to a centre. With two processing layers, the input is mapped onto each node in the hidden layer and the output layer is a linear combination of hidden layer outputs multiplied by their weights. In classification problems the output layer is typically a sigmoid function of a linear combination of hidden layer values, representing a posterior probability.

Various ECG classification techniques have been recently discussed. Gerardo (2006) utilize hybrid neuronal-fuzzy networks to quantify and characterize the heart rate variability (HRV). Similarly, Lu (2000), proposes neuro-fuzzy system to diagnose acute myocardial infarction (AMI). Statistical methods, such as Markov model was also discussed in (Messadeg, 2006) to classify some cardiac. In this paper, sparsely connected RBFNN is explored to detect the PQRST wave consisting of five features extracted using wavelet decomposition method.

## 2. Sparsely Connected RBFNN

The strength of RBFNN lies in its highly accurate classification, low memory requirement and faster learning time (Le et al, 1994). RBF networks have the disadvantage of requiring good coverage of the input space by radial basis functions. RBF centers are determined with reference to the distribution of the input data, as a result, representational resources may be wasted on areas of the input space that are irrelevant to the learning task. Therefore, in this work, sparsely connected RBF is used to effectively classifying the signals. Figure 1 shows the structure of sparsely connected RBFNN.

## 3. ECG Signal

ECG signal is generated by rhythamic contractions of the heart measured by electrodes. This signal can be effectively used for heart disease diagnosis. The analysis problem can be divided into two parts, the feature extraction and classification. The feature extraction procedure is necessary to detect abnormality of the signal, while the classification procedure is used to distinguish disease types. The ECG signal is made up of a group of repetative PQRST signals. The normal class of PQRST is as shown in Figure 2.

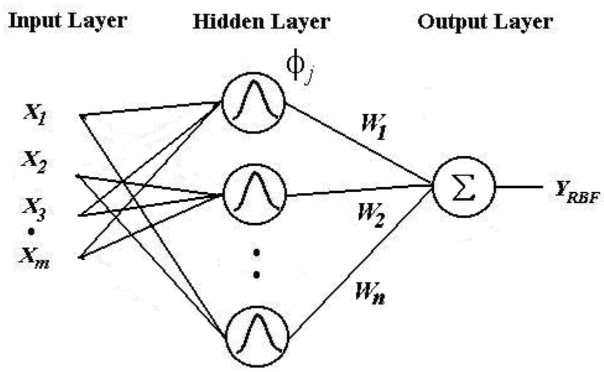


Fig. 1 Sparsely connected RBFNN

Three classes of ECG signals have been selected for the classification tasks; the normal sinus rhythm, malignant ventricular ectopy and atrial fibrillation. The malignant ventricular ectopy and atrial fibrillation is chosen because they are commonly found in arrhythmia cases (Lip, 2001). These two classes of ECG signal falls into “not healthy” category that contributes from heart problems and blood-related diseases. The shape of the PQRST wave differs in different classes of ECG signals. Hence, unique features of each class of ECG signal need to be identified for efficient classification process. These two procedures, feature extraction and classification of ECG signal, significantly contribute to clinical diagnosis of heart-related diseases.

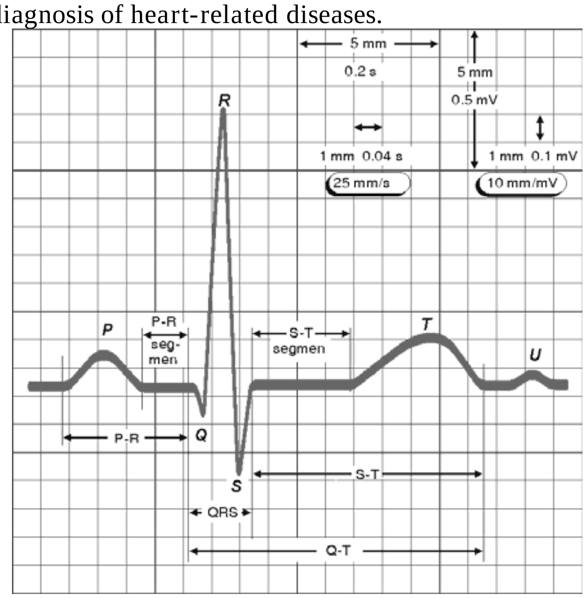


Fig. 2 Normal PQRST wave

The diagnosis of quality analysis is based on the Silipo (1996). In general, there are four categories that represent the diagnosis classes. They are;

True positive for diseasae A = positive test for disease A
False negative for disease A = negative test for disease A
False positive for disease A = positive test not for disease A
True negative for disease A = negative test not for disease A

An effective diagnosis test and ECG classification should be able to minimise the number of false negatives and false postives. The quality evaluation analysis is used in probability aspect of sensitivity and ceratinty levels. Sensitivity level represents the probability of one test producing positive result of disease A for patient beloging to the group with disease A. On the hand, the certainty level represents the probability of one test producing negative result of disease A for patient not having disease A.

## 4. Methodology

Three classes of ECG signals in this study are the normal sinus rhythm, malignant ventricular ectopy and atrial fibrillation. From the web site of Physionet, the data base provides 23 atrial fibrillation type, 22 of malignant ventricular ectopy type and 18 of normal sinus rhythm type. The signals from the three classes are sampled at the rate of 128 samples per second. Input nodes of the network can be very large (about 7680) if all points are taken into consideration in determination of the classes, while the connections between the nodes will be a few times larger than the input nodes. Feature extraction process help to overcome this problem. Five feature representations have been developed to replace the input signal that constitutes all the data points for the neural network. These feature representations involve one set of PQRST-wave from a series of PQRST-waves in a period of one second. To extract accurate information from each set of ECG data, five sets of PQRST-wave from different locations in one ECG signal were extracted. The selection of PQRST-wave sets were based on five places of R-wave at its maximum in a series of ECG signal. One set of extracted PQRST-wave comprise of 91 data points and maximum R-wave at point 41. This size is suitable to represent all PQRST-wave because in normal case, PR interval is close to 0.2 second (25 samples), while QT interval is 0.42 seconds (53 samples) as shown in Figure 1 (a). The PQRST-wave that is necessary to be extracted is as shown in Figure 3.

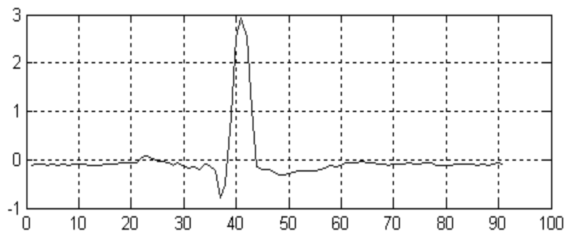


Fig. 3 Required extracted PQRST wave

For every ECG data, five sets of PQRST-wave were extracted using wavelet decomposition technique. This technique would detect the location of maximum R-wave, P-wave and QS-wave. P, R and QS-wave detection provides valuable information found in the interval and amplitude of ECG signal (Mahmoodabadi et al, 2005). The Daubechies wavelet was used in this study because it provides more information and complex computation. Wavelet decomposition would disintegrate the original wave into eight elements of signal components at different frequency bands. The element of signal components at level three to five (medium frequency band range) is used to project the R-wave characteristics and features. The original signal is as shown in Figure 4 a) and b). Figure 3 c) shows the signal without the low frequency components. The rest of the signals indicate the detection of R-wave, QS-wave and PT-wave after wavelet decomposition procedure and the integration of suitable component selection process were performed.


Fig. 4 PQRST wave detection for one sample of ECG signal

The QS-wave is represented by element of signal more than level 5 (high frequency band range). The projection of P and T waves require the elements of signal component from level four to eight. Overall, this technique is appropriate to be used in feature extraction applications due to its high detection accuracy (Mahmoodabadi et al, 2005).

The extraction of feature representations involves the detection of QRS complex rate, P and R wave amplitude, the distance between Q and S wave and finally, the minimum T point. The detection of QRS complex rate was used to project ECG atrial fibrillation type. In this class, the QRS complex rate is very irregular (Lip, 2001). In malignant ventricular ectopy and atrial fibrillation types, the R wave amplitude is negative.

## 5. Results And Discussions

The ECG data were divided into smaller groups as indicated in Table 1. Matlab programming codes were developed to select two axes for feature representations to produce maximum group size with minimal number of iterations. Only training data were used in detecting the location of centers and the radius of clustered data. The center prototypes were the summation of the mean value for every dimension of data within the same smaller groups which is similar to clustering technique. The radius, center prototypes and two main feature representations were saved in a matrix referred to as *center*.

The program '*radii*' was developed in this work that produces the parameters shown in Table 2. Table 3 shows the result on the accuracy of the test data using the sparsely connected RBFNN. The overall result in comparing the classification accuracy between sparsely connected RBFNN, the conventional RBFNN and LDA is shown in Table 4.

## 6. Conclusions

Based on the results, it can be concluded that sparsely connected RBFNN can accurately classify ECG signals into normal sinus rhythm and malignant ventricular ectopy. Due to varied features of atrial fibrillation type, the classification process is less effective compared to the other two types. The hidden nodes of the network represent all smaller groups from each ECG classes that emphasize on the different feature representations during classification process. Therefore, the partial connectivities between the nodes reduces the computational complexities and increases the learning rate.

The wavelet decomposition technique used in feature extraction process performed satisfactorily to effectively project P, Q, R, S and T waves from original ECG signal.

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Table 1 ECG data in smaller groups

| Classes of Data | Main axis | Second axis |
|---|---|---|
| Atrial Fibrillation | | |
| 6,7,15,18,20,22 | *R-R* Standard deviation | *QS* distance |
| 11,13,14,16,19,23 | *R-R* Standard deviation | Minimum *T* point |
| 4,9,12 | *R-R* Standard deviation | ECG amplitude |
| 2,3,5,21 | *R-R* Standard deviation | *QS* distance |
| 1, 10 | *R-R* Standard deviation | Gelombang *P* |
| Normal Sinus Rhythm | | |
| 2,4,5,6,7,8,13,14,15,16,17,18 | *QS* distance | *P*- wave |
| 3,9,10,11,12 | *QS* distance | *R-R* Standard deviation |
| Malignant Ventricular Ectopy | | |
| 2,8,13,14,18,20,21 | *QS* distance | *R-R* Standard deviation |
| 1,5,15,16,17 | *QS* distance | *R-R* Standard deviation |
| 3,4,6,9,11 | *QS* distance | *R-R* Standard deviation |
| 7,10,12,22 | *QS* distance | *P*- wave |

Table 2 Parameters for center matrix

| No of center prototypes | Radius | Center of main axis | Center of second axis | Main feature representation | Second feature representation |
|---|---|---|---|---|---|
| 1 | 0.22 | 0.9524 | 0.3175 | *R-R* | *QS* |
| 2 | 0.13 | 0.3325 | 0.8738 | *R-R* | *T* |
| 3 | 0.07 | 0.0363 | 0.1669 | *R-R* | *R* |
| 4 | 0.03 | 0.0536 | 0.2332 | *R-R* | *QS* |
| 5 | 0.26 | 0.5063 | 0.4242 | *R-R* | *P* |
| 6 | 0.07 | 0.0810 | 0.1439 | *QS* | *P* |
| 7 | 0.04 | 0.1911 | 0.1098 | *QS* | *R-R* |
| 8 | 0.27 | 0.7127 | 0.7471 | *QS* | *R-R* |
| 9 | 0.14 | 0.8746 | 0.0367 | *QS* | *R-R* |
| 10 | 0.06 | 0.3596 | 0.0976 | *QS* | *R-R* |
| 11 | 0.09 | 0.5151 | 0.0634 | *QS* | *P* |

Table 3. Result on accuracy of test data

| ECG Classes | AFB | NOR | MVE |
|---|---|---|---|
| Atrial Fibrillation, AFB | **9** | 2 | 1 |
| Normal Sinus Rhythm, NOR | 0 | **9** | 0 |
| Malignant Ventricular Ectopy, MVE | 0 | 0 | **12** |

Table 4 Overall result based on the three methods

| Method | AFB | | NOR | | MVE | |
|---|---|---|---|---|---|---|
| | Sensitivity (%) | Certainty (%) | Sensitivity (%) | Certainty (%) | Sensitivity (%) | Certainty (%) |
| Sparsely Connected RBFNN | 75 | 100 | 100 | 91.7 | 100 | 95.2 |
| Conventional RBFNN | 54.5 | 90.0 | 88.9 | 81.8 | 90.9 | 95.0 |
| LDA | 58.3 | 76.2 | 100 | 79.2 | 41.7 | 90.5 |