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# Personalized ECG Signal Classification Using Block-Based Neural-Network and Particle Swarm Optimization

Shirin Shadmand
Microelectronics Research Laboratory,
Electrical Engineering Department,
Urmia University, Urmia, Iran
st_s.shadmand@urmia.ac.ir

Behbood Mashoufi
Microelectronics Research Laboratory,
Electrical Engineering Department,
Urmia University, Urmia, Iran
b.mashoufi@urmia.ac.ir

***Abstract*— The purpose of this paper is the classification of ECG heartbeats of a specific patient in five heartbeat types according to AAMI recommendation, using an implementable neural network such as Block-based Neural Network (BBNN). A BBNN is created from 2-D array of blocks that are connected to each other and easily can be expanded. Each block is a neural network. Because of flexibility in structure and internal configurations of BBNN, we can implement that with a reconfigurable digital hardware such as field programmable gate array (FPGA). The internal structure of each block depends on number of incoming and outgoing signals. Therefore, the overall construction of network is determined by the moving of signal through the network blocks. Network structure and the weights are optimized using particle swarm optimization (PSO) algorithm. Input of the BBNN is a vector that the elements of this vector are the features that extracted from ECG signal. In this paper wavelet transform based features and temporal features that extracted from ECG signals create the input vector of BBNN. ECG signals are time varying and also for different people are unique. The BBNN parameters have been optimized by PSO algorithm witch can overcome the possible changes of ECG signals. The performance evaluation using the MIT-BIH arrhythmia database shows a high classification accuracy of 97 %.**

***Keywords- Block-based Neural Network (BbNNs); Particle Swarm Optimization (PSO); Electrocardiogram signals (ECG); Patient specific ECG signal classification.***

## I. Introduction

Electrocardiography (ECG) shows the electrical activity of heart over a period of time when an electrical signal is applied in a point of the body and is read out from another point. ECG signals vary greatly for different individuals [1]. Also some physical conditions cause ECG signals to change for the same individuals over the time.

Because of dynamic nature of ECG signals, a fixed structure classifier cannot be used. Therefore, we have to use an evolvable classifier which changes the internal parameters to satisfy the dynamic nature of ECG signals. Some of the methods for ECG signal classification have been presented in the literature.

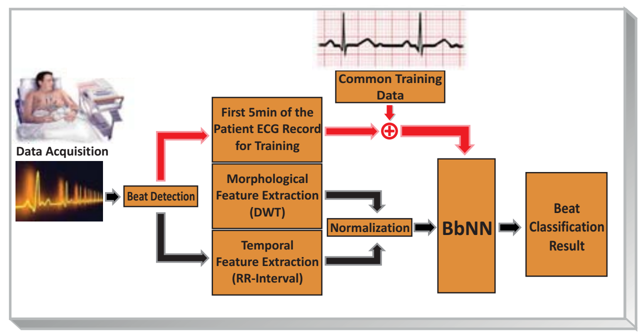


Fig.1 ECG signal classification steps

These methods need to extract some features from ECG signals, such as heartbeat temporal features [2], morphological features [2], frequency domain features [3] and coefficients of wavelet trasformation [4]. The methods used in this literature for ECG signal classification, include support vector machines [5], hidden Markov models [6], mixture-of-experts method [7] and artificial neural networks (ANNs) [8]. Because of this dynamic nature of ECG signals, the methods with fixed network structure [8] do not represent an optimal solution for classification.

In this paper, we use an evolvable neural network (NN) [9] which its parameters (structure and internal configuration) are modified based on the changes of ECG signals. For designing an artificial NN, there are two issues. First issue is simultaneous optimization of the structure and corresponding weights. Second issue is hardware implementation of NNs. Block-based Neural Network (BBNN) [10] can tackle these issues. The internal weights and overall structure of BBNN can be represented by a vector. Although using this method the network structure and weights can be optimized simultaneously.

Particle Swarm Optimization (PSO) [11] is an algorithm used in this paper for training and optimization tasks. This algorithm which is based on birds flocking behavior for finding food, uses swarm intelligence for finding optimal solution for problems. The birds flocking movement to find food is equal to create a swarm of solutions for a problem and the food resource is equal to the best solution. In this algorithm all members of swarm have two parameters; position and velocity. At first, these parameters are initialized with random numbers. The swarm of solutions is named particles. Each particle in this algorithm, changes its position and velocity until finding optimal solution. All particles are in contact with each other. To achieve an optimal solution, they change their positions according to best position of each particle itself (local best) and population best position (global best).

This paper presents a classification method using BBNN neural network as a classifier and PSO algorithm as a training algorithm and finding an optimal structure for BBNN. In this paper, ECG signals are classified in five groups (a normal group and four abnormal groups). The classifier designed for ECG signals classification, is unique for each person. The BBNNs use the morphological (wavelet based features) and temporal (RR-interval ratio) features that extracted from the ECG signals. The developed BBNN has 97% accuracy for classification of the ECG test records that are selected from MIT-BIH arrhythmia database. The steps for ECG signal classification is shown in fig.1.

## II. BBNN AS A CLASSIFIER

A Block-based Neural Network [10] represents by a structure of blocks in two dimensions. Each block is a small neural network with one input layer and one output layer (without any hidden layer). There are four neighboring blocks around each block and it is connected to them with signal flows. In other words, outputs of each block are connected to the inputs of neighbors. The firs block and last block in each row have also a connection one another. The overall construction of network and internal structure of all blocks are determined simultaneously by the moving of signal through the network blocks. Fig.2 represents the BBNN structure by size of $m \times n$ that $m$ and $n$ are numbers of network rows and columns, respectively.

Each block is labeled as $B_{mn}$ that specifies the block position ($m$th row and $n$th column). The input vector ($x$) goes in to the network by input blocks and the output vector ($y$) goes out from output blocks. The BBNN can have a multiple number of middle layers. In Fig.2, $x_i$ ($i$=1, 2,…, n) and $y_j$ ($j$=1, 2,…, m) are network inputs and outputs, respectively. The input signal $x$, flows through the blocks and produces the output signal $y$.

Because of modular property of BBNN, it can be grows larger by adding extra blocks. In this paper a BBNN with downward signal flow is used to facilitate hardware implementation. A BBNN with feedback signal flow produces the outputs with longer delay, so prompting the network needs for extra hardware resources [12].

There are three different types for internal configuration of a BBNN that are shown in Fig.3. Each block has four nodes that are connected to each other. Some nodes are input and some are output. Fig.3 shows four different blocks: 1. three input nodes and one output node, 2. one input node and three output nodes, 3. two types for blocks with two input nodes and two output nodes. Input and output nodes are connected to each other with weighted connections. A weight $w_{ij}$ denotes a connection from node $i$ to node $j$. The output nodes also have a bias weight. Although, a block can has at least four connection weights for the case of three inputs and one output and maximum connection weights can be six for the cases of two inputs with two outputs and one input with three outputs .

Direction of signal flow between the nodes, determines type of nodes. When an arrow is incoming to a node, that is

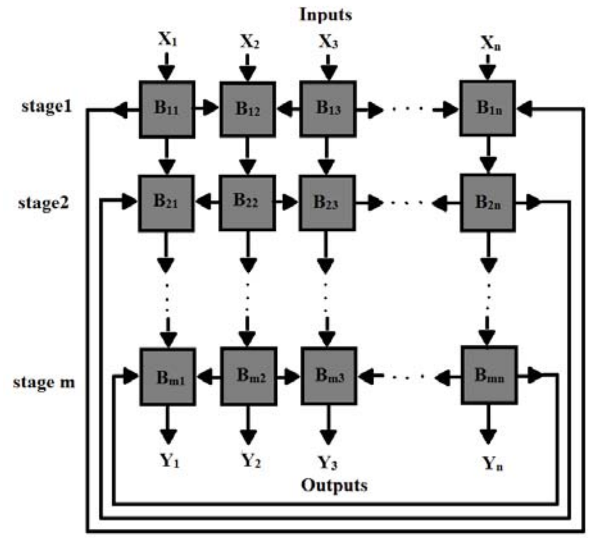


Fig.2. Structure of Block-Based Neural Network (BBNN)

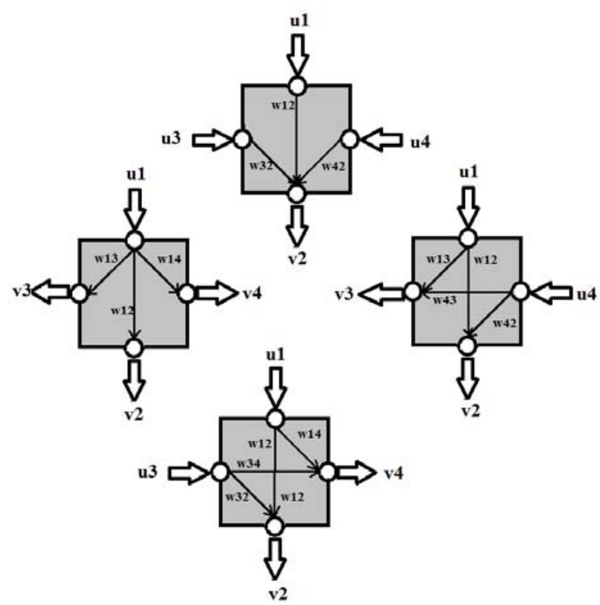


Fig.3. Four type of BBNN internal con figuration

input and an outgoing arrow from a node, specifies the node is an output.

Each output node uses an activation function h(*). After summation of weighted inputs and bias weight, the result passes from this activation function and creates output of the block.

The signals $u_i$ and $v_j$ represent input and output signals of a block. The output nodes have an activation function h(*).

$$v_j = h\left(g_j\right),\ j \in J.$$

$$g_j = \sum_{i \in I} \omega_{ij} u_i + b_j \tag{1}$$

$I$ and $J$ denote the indexes of input and output nodes, respectively. $g_j$ is output of node before activation function. $b_j$ is the bias of the $j$th node. In this paper, the final output of each block is produced by fallowing function.

$$h(x) = \left(\frac{2}{1+e^{-2x}} - 1\right) \tag{2}$$

## III. ECG SIGNAL CLASSIFICATION

### A. ECG Data

In this paper for training and testing the classifier that is used for ECG signal classification, the MIT-BIH arrhythmia database [13] is used. This database contains 48 records that are obtained from 47 individuals. Each record contains two channels (MLII and V5) ECG signals for 30 minutes duration that is selected from 24-hours recordings. Continues ECG signals were band pass-filtered using a filter with a passband from 0.1 to 100 Hz, then were converted to digital data.

Each record in this database also has an annotation file. Information about the occurrence time of heartbeat (R-peak location) or beat class information is in this file. With considering 100 samples around the R-peak we can detect the heartbeats. In this database four records that have paced beats are excluded and remaining 44 records are used.

The first 20 records (numbered from 100-124) include representative samples of routine clinical recordings and we have used them as common training set. The remaining 24 records (numbered from 200-234) contain some unusual beats such as ventricular and supraventricular arrhythmias. We have used these records as testing set.

In this study we have used modified-lead II (MLII) signals for all records. According to AAMI recommendation, each ECG beat can be classified into one of five different classes. Each class shows one type of heartbeats and are shown with N (normal beats), VEB (ventricular ectopic beats), SVEB (supra ventricular ectopic beats), F (fusion beats) and Q (unclassifiable beats).

Because of ECG signals variation for different persons, a unique classifier (BBNN) is designed for each person. This NN is trained with two sets of training sets. First set is common for all persons and consists of 200 sample beats that randomly selected from records 100 to 124 (60 samples for N, 60 samples for VEB, 60 samples for SVEB, all 13 samples for F and all 7 samples for Q). The second set contains all the samples in first 5 minutes of each person ECG record [14].

The remaining records (200 to 234) are used in testing set for performance evaluation of classification.

### B. Feature extraction

For each ECG heartbeat a feature vector is extracted that represents some features of signal such as morphological or temporal features. In this paper both morphological and temporal features are combined for each heartbeat.

The morphological features are extracted using discrete wavelet transformation and temporal feature that is used in this paper, is RR-interval ratio. These features are described in the following section.

### C. Discrete wavelet transformation (DWT)

The discrete wavelet transformation is one of effective tools for extracting some useful features in signal processing field. DWT provides clear time resolution at high frequency and clear frequency resolution at low frequency. Because of its great time and frequency localization ability, the DWT can reveal the local characteristics of the input signal [14], [7]-[9].

Wavelet has four families: Daubechies, Biorthogonal, coiflets and symlets. These families differ in shape of wavelet but generally they are same. It is important to select an appropriate wavelet for specific signal processing. Appropriate wavelet should have a similar wave shape to the signal to be analyzed [15], therefore we select the Daubechies family in this paper because its shape is very close to ECG signals.

Wavelet transformation is convolving the wavelet function with the original signal. Wavelet transformation is same as filtering the signal with a high-pass filter and a low-pass filter. These filters decompose signal to approximate information (result from low-pass filter) and detail information (result from high-pass filter).

Fig.4 shows the wavelet decomposition levels for record 200. In this study we used the 7-level discrete wavelet decomposition. The first and second level of DWT (cd1, cd2), include the low frequency noise information in the range 0 Hz to 50 Hz. This information is not important, therefore we can spare from them. Also the levels cd3 and cd4 are spared because they make the signal jagged after reconstruction of signal.

Therefore we used only three levels of wavelet decomposition (cd5, cd6 and cd7) for create feature vector at the end of this process. Feature vector is created with fifteen features that shown in table I.

A temporal feature is also added to feature vector to improve the performance of classification, therefore we add RR-interval ratio (IR) as a temporal feature to our feature vector.

TABLE I. EXTRACTED WAVELET FEATURE

| Wavelet feature | For cd5, cd6, cd7 |
|---|---|
| Mean | $w_1$, $w_2$, $w_3$ |
| Variance | $w_4$, $w_5$, $w_6$ |
| Maximum | $w_7$, $w_8$, $w_9$ |
| Median | $w_{10}$, $w_{11}$, $w_{12}$ |
| Sum (absolute (.)) | $w_{13}$, $w_{14}$, $w_{15}$ |

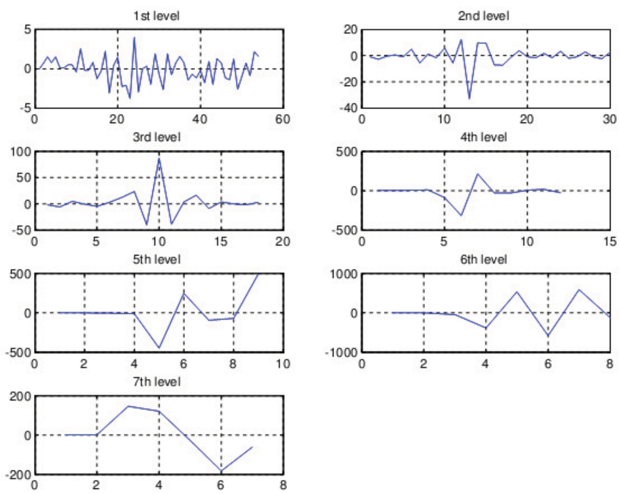


Fig.4. The wavelet decomposition levels for record 200.

$$IR_i = \frac{T_i - T_{i-1}}{T_{i+1} - T_i} \quad (3)$$

Where $T_i$ is the R-peak occurrence time for beat $i$ .This feature vector (temporal and morphological feature) is the BBNN input.

## IV. PSO ALGORITHM FOR AUTOMATIC BBNN DESIGN

### A. *PSO algorithm:*

Particle swarm optimization was first introduced by Dr. Russell C. Eberhart and Dr. James Kennedy in 1995. In this algorithm, a population of particles adapts by returning stochastically toward previously successful regions [11].

PSO has two important parameters: velocity and position. During the optimization these operators will be updated and each particle is accelerated toward the particles previous best position and the global best position. At each generation a new velocity and position is calculated for each particle according following equations.

$$v_i(t) = \chi\{v_i(t-1) + c_1 r_1 (pbest_i - x_i(t-1)) + c_2 r_2 (gbest - x_i(t-1))\} \quad (4)$$

$$x_i(t) = x_i(t-1) + v_i(t) \quad (5)$$

$$\chi = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \quad (6)$$

In this equation $\chi$ is construction coefficient was developed by Clerc in 2000 [16]. Using a construction coefficient causes particles to quickly convergence over time. The amplitude of the particles oscillations decrease as it focuses on the local and global previous best position. Though, the particle converges to a point over time.

If the previous local and global best positions are near each other, the particle will perform a local search with small steps. If the previous local and global best positions are far apart from each other, the particle will perform a global search with big steps. During the search, global best position and previous best position for each particle will change and particle will shift from local search back to global search.

Clerc, *et al.* found that by modifying $\varphi$ the convergence characteristics of the system can be controlled. In this paper $c_1$ and $c_2$ are set to 2.05 and $\varphi$ is set to 4.1.

The new velocity value is calculated based on current velocity value of particle, the distance from its previous best position and distance from the global best position. This process is then repeated until finishing a set number of times or achieving to a minimum error.

### B. *PSO fitness function:*

Fitness function for ECG signal classification task should evaluate the performance of the classification that found by PSO. The fitness function for evaluation of the BBNN for one person is defined as:

$$fitness = \frac{\beta}{1 + \frac{1}{n_O M_1}\sum_{t=1}^{M_1}\left\|d_c^l - y_c^l\right\|} + \frac{1-\beta}{1 + \frac{1}{n_O M_2}\sum_{t=1}^{M_2}\left\|d_s^l - y_s^l\right\|} \quad (7)$$

$M_1$ and $M_2$ denote the number of samples in the common and patient specific training data, respectively. The $d^l$ and $y^l$ are two vectors that show the target and actual outputs for the $l$th training pattern, respectively. $n_o$ denotes the number of output blocks. $\beta$ determines the impression ratio of common and patient-specific training sets in the final fitness function. A small value of $\beta$ less than 0.5 causes the effect of patient-specific training set to be major and the designed BBNN to be specific for a patient [12].

## V. CLASSIFICATION PERFORMANCE

In this paper for training the BBNN, the common training set contains a total of 200 representative beats, including 60 beats from each type-N, -S, and -V, all 13 type-F and 7 type-Q. These beats are randomly selected from records 100 to 124 for each class. Another training set contains all beats that are in first five minutes of each person's ECG record and includes a variable number of beats for each person.

We performed classification experiments on 7 records of 22 test records, which include 12822 beats that are classified into five different classes. According to AAMI these classes are N, S, V, F and Q. [17]

Table II shows classification results for 12822 test beats.

TABLE II. BEAT-BY-BEAT SIGNAL CLASSIFICATION

| Truth | Classification result | | | | |
|---|---|---|---|---|---|
| | *N* | *S* | *V* | *F* | *Q* |
| ***N*** | 9782 | 0 | 32 | 0 | 0 |
| ***S*** | 25 | 188 | 0 | 0 | 0 |
| ***V*** | 187 | 64 | 1751 | 0 | 0 |
| ***F*** | 62 | 0 | 37 | 105 | 0 |
| ***Q*** | 6 | 0 | 0 | 0 | 0 |

According to AAMI, four fundamental measurements that show the Classification performance are classification accuracy (Acc), sensitivity (Sen), specificity (Spe), and positive predictively (Ppr) [14]. These parameters are shown in below.

$$Acc = \frac{\text{true positive + true negetive}}{\text{true positive + tru negetive +false positive + false negetive}} \quad (8)$$

$$Sen = \frac{\text{true positive}}{\text{true positive + false negetive}} \quad (9)$$

$$Spe = \frac{\text{true negetive}}{\text{true negetive + false positive}} \quad (10)$$

$$Ppr = \frac{\text{true positive}}{\text{true positive+ false positive}} \quad (11)$$

The performance results for SVEB detection are shown in Table III, and are compared with two previous works that are common in classifier type or classification method.

TABLE III. CLASSIFICATION RESULTS FOR SVEB BEATS FINDING IN PROPOSED AND TWO SIMILAR METHODES

| Methods | SVEB | | | |
|---|---|---|---|---|
| | *Acc* | *Sen* | *Spe* | *Ppr* |
| Chazal et al.[2] | 92.4 | 76.4 | 93.2 | 38.7 |
| Ince, Kiranyaz and Gabbouj [14] | 96.1 | 81.8 | 98.5 | 63.4 |
| Proposed | 96.6 | 88.3 | 99.5 | 74.6 |

## VI. CONCLUSION

In this paper, we proposed a classification system for personalized ECG signal classification that uses block-based neural network as classifier and particle swarm optimization algorithm that trains the BBNN and optimizes network structure and connection weights, simultaneously. The input of BBNN is a vector of features that are extracted from ECG signals. The DWT is used for morphological features extraction from ECG heartbeats. Also, a temporal feature (RR-interval ratio) is combined with morphological features.

The BBNN trained with PSO algorithm, presents a high quality classification system for electrocardiogram records. The reporting of results shows that the accuracy, sensitivity, specificity and predictivity of SVEB finding for this research are 96.62 %, 88.26 %, 99.45 %, 74.6 %, respectively. These consequences show an obvious recovery compared to [2] and [14] for SVEB beats finding. The classifier that is used in this paper is very useful for dynamic problems which need an evolvable solution through tackle possible changes.

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