Median M-Type Radial Basis Function Neural Network for Image Classification Applications

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Abstract. We present the Median M-Type Radial Basis Function (MMRBF) neural network for image classification applications. The proposed neural network uses the Median M-type (MM) estimator in the scheme of radial basis function to train the neural network. Extensive simulation results have demonstrated that the proposed MMRBF neural network consistently outperforms other RBF algorithms in terms of classification capabilities.

1 Introduction

In recent years neural computing has emerged as a practical technology, with successful applications in several fields. These applications are concerned with problems in pattern recognition, and make use of feed-forward network architectures such as the multi-layer perceptron and the radial basis function network [1,2].

The Radial Basis Functions (RBF) have been used in several applications for pattern classification and functional modeling [3]. These functions have been found to have very good functional approximation capabilities [3]. The RBF have their fundamentals drawn from probability function estimation theory.

The RBF network involves three layers with entirely different roles [4-6]. The input layer is made up of source nodes that connect the network to its environment. The second layer is the only hidden layer in the network, applies a nonlinear transformation from the input space to the hidden space. The output layer is linear, supplying the response of the network to the activation signal or pattern applied to the input layer

In this paper, we present the use of the Median M-Type (MM) estimator with different influence functions [7] as statistic estimation in the Radial Basis Function network architecture for image classification purposes. Extensive simulation results have demonstrated that the proposed MMRBF neural network consistently outperforms other RBF algorithms in terms of classification capabilities.

A. Gelbukh, S. Suárez, H. Calvo (Eds.)
Advances in Computer Science and Engineering
Research in Computing Science 29, 2007, pp. 81-89

Received 05/07/07
Accepted 19/10/07
Final version 24/10/07

2 Proposed MMRBF Neural Network

In the RBF neural network each of N_k components of the input vector **X** feeds forward to M basis functions whose outputs are linearly combined with weights $\{\lambda_j\}_{j=1}^{M}$ into the network output $Y_k(\mathbf{X})$ [4-6]. Figure 1 presents the structure of the RBF neural network.

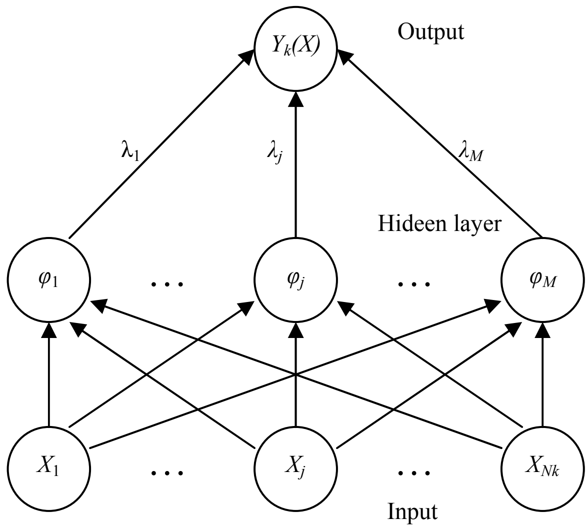


Fig. 1. Radial Basis Function Neural Network architecture.

The inverse multiquadratic function is used as activation function in the proposed MMRBF neural network [5],

$$\phi_j(\mathbf{X}) = \frac{1}{\sqrt{\mathbf{X}^2 + \beta_j^2}} \tag{1}$$

where **X** is the input feature vector, β_j is a real constant. In our simulation results β_j=1.

A combined unsupervised-supervised learning technique has been used in order to estimate the RBF parameters [5].

In the unsupervised stage, the k-means clustering algorithm is used to estimate the parameters of the MMRBF neural network [1,2]. The input feature vector **X** is classified in k different clusters. A new vector **x** is assigned to the cluster k whose centroid μ_k is the closest one to the vector. The centroids can be updated at the end of several iterations or after the test of each new vector, and they can be calculated with or without the new vector. The centroid vector is updated in the following way [8,9]

$$\mu_k = \mu_k + \frac{1}{N_k}(\mathbf{x} - \mu_k) \tag{2}$$

where N_k is the number of vectors already assigned to the k-cluster.

The Hard limit transfer function is used in the supervised stage to calculate the weights coefficients in the neural network [1,2].

$$\text{hardlim}(x) = \begin{cases} 1, & x \geq 0 \\ -1, & \text{otherwise} \end{cases} \tag{3}$$

The Median M-type (MM) estimator [7] is used in the proposal RBF neural network as robust statistics estimate of a cluster center,

$$\mu_k = \text{med}\{\mathbf{X}\tilde{\psi}(\mathbf{X} - \theta)\} \tag{4}$$

where $\mathbf{X}$ is the input data sample, $\theta = \text{med}\{X_k\}$ is the initial estimate, $\tilde{\psi}$ is the normalized influence function $\psi : \psi(\mathbf{X}) = \mathbf{X}\tilde{\psi}(\mathbf{X})$, k=1, 2,…,N_k, and the influence functions used are the following [7]:
the simple cut (skipped mean) influence function,

$$\psi_{\text{cut}(r)}(X) = \begin{cases} X, & |X| \leq r \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

and the Tukey biweight influence function,

$$\psi_{\text{bi}(r)}(X) = \begin{cases} X^2(r^2 - X^2), & |X| \leq r \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

where X is a data sample and r is a real constant and depends of the data to process and can change for different influence functions.

3 Experimental Results

We obtained from the simulation experiments the properties of proposed Median M-Type Radial Basis Function (MMRBF) neural network with simple cut (sc) and Tukey biweight (tb) influence functions, and its performance has been compared with the Simple RBF (SRBF), Median RBF (ATMRBF) [8], and α-Trimmed Mean RBF (MRBF) neural networks [9].

To determine the classification properties of proposed Median M-Type Radial Basis Function (MMRBF) neural network and other RBF networks used as comparative we apply them to mammographic image analysis [10,11]. The images used to train and probe the RBF neural networks were obtained from the Mammographic Image Analysis Society (MIAS) web site [12]. Table 1 shows the number of images used in the stages of training and probe and the groups used to classify different mammographic images.

Table 1. Groups of mammographic images used to train and probe different RBF neural networks.

Group	Mammographic Images	Training	Probe
A	normal	8	40
	benign abnormalities	8	38
B	malign abnormalities	8	30
	benign microcalcifications	4	8
	malign microcalcifications	4	9

The criteria used to compare the performance of neural networks were the efficiency and error,

$$efficiency = \frac{\#\ of\ right\ \ probes}{total\ of\ i\ mages} \text{ x } 100\% \tag{7}$$

$$error = \frac{\#\ of\ errores}{total\ of\ images} \text{ x } 100\% \tag{8}$$

Therefore, to evaluate the performance of the neural networks in terms of medical purposes, we calculated two quantities [13]:
the *sensitivity* is the probability that a medical test delivers a positive result when a group of patients with certain illness is under study [13],

$$Sn = TP / (TP + FN) \tag{9}$$

and the *specificity* is the probability that a medical test delivers a negative result when a group of patients under study do not have certain illness [13],

$$Sp = TN / (TN + FP) \tag{10}$$

where Sn is the *sensitivity*, TP is the number of true positive that are correct, FN is the number of false negatives, that is, the negative results that are not correct, Sp is the *specificity*, TN is the number of negative results that are correct, and FP is the number of false positives, that is, the positive results that are not correct.

Figure 2 presents the performance results in terms of efficiency and error for the classification of mammographic images in the groups A and B (see Table 1). In this Figure one can see that the best results are obtained when we use the proposed MMRBF neural network.

Table 2 show the comparison between different RBF algorithms used in the mammographic image analysis. We observe from this Table that the proposed MMRBF neural network has the best efficiency in the probe stage in the most of the cases.

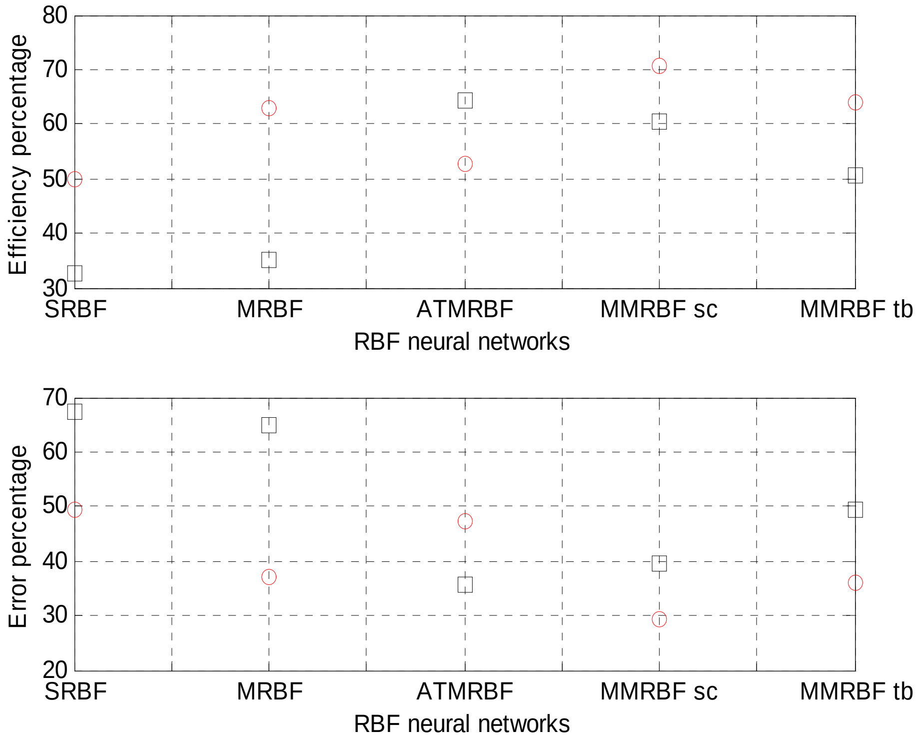


Fig. 2. Performance results of efficiency and error by group obtained by different neural networks, the red circle and black square indicate the group A and B, respectively.

Table 2. Efficiency results between the MMRBF and other algorithms used as comparative in the probe stage.

Neural Networks	SRBF	MRBF	ATMRBF
MMRBF sc	24.90%	18.22%	4.80%
MMRBF tb	16.38%	9.70%	-3.72%

Table 3 presents the *sensitivity* and *specificity* values obtained for different RBF neural networks. It can be appreciated that the specificity of the proposed MMRBF using simple cut influence function is the highest one, about a 20% above ATMRBF, but this last network has the best sensitivity, about 10% above the mentioned MMRBF sc.

Table 3. Sensitivity and specificity values for different RBF neural networks.

Neural Networks	Sensitivity	Specificity
SRBF	34.04%	50.00%
MRBF	31.91%	62.82%
ATMRBF	57.45%	52.56%
MMRBF simple cut	48.93%	70.51%
MMRBF Tukey	44.68%	64.10%

Figure 3 shows the visual results in the process of segmentation of mammographic images, with these images the proposed network realizes the classification of them into two groups (A and B). We notice that the error in the classification can be minimized by means of use other algorithms in the segmentation stage due that the mammography images are very irregular and it can cause false positive and false negative results. Figure 4 shows a mammographic image that corresponds to a proper result in terms of classification. In this case the proposed MMRBF neural network provides a better classification in comparison with other RBF networks. Figure 5 presents the case of an improper result due that some mammographic images are not regular.

In our experiments also was measured the time necessary for the system to deliver a result. We used a DELL ® Precision 380 PC, which has a Pentium 4 Intel® processor running at 3 GHz and 2GB RAM memory. The time to classify an image was measured in 65 images of 1024x1024 pixels and 8 bits per pixel. Table 4 shows the average processing time of the main stages of classification process.

Table 4. Average processing time (in minutes) for the main stages in the proposed method.

	Average time	% of total time
Segmentation and Feature Extraction	30.307	99.85
MMRBF Classifier	0.044	0.15

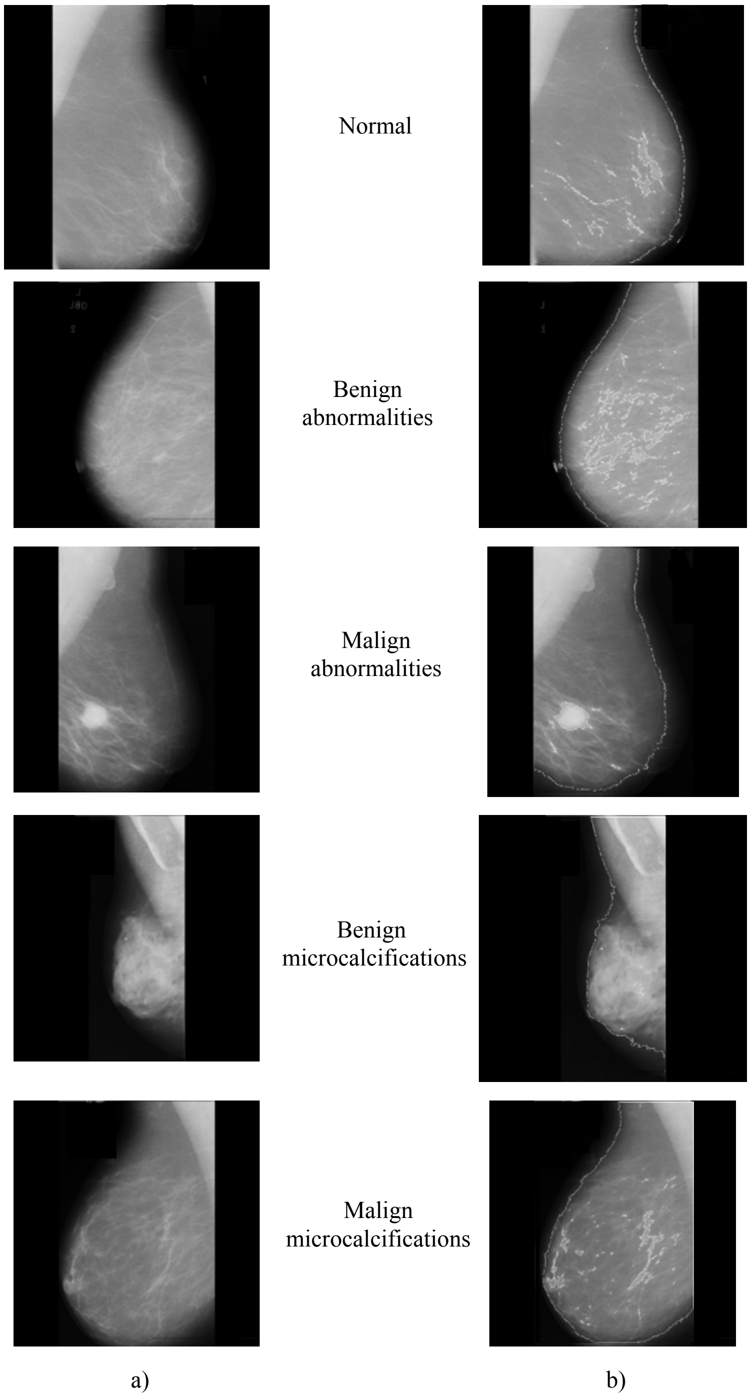
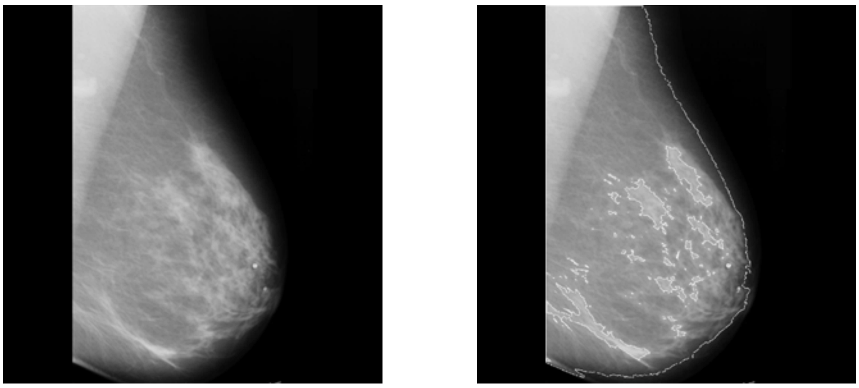


Fig. 3. Visual results in the classification of mammographic images, a) original images and b) segmented images.

a) Original image b) Segmented image

Fig. 4. Visual result of mammography image with a proper result in the classification of mammographic images.



a) Original image b) Segmented image

Fig. 5. Visual result of mammography image with an improper result in the classification of mammographic images.

4 Conclusions

In this paper we present the MMRBF neural network, it uses the MM-estimator with different influence functions in the scheme of radial basis function to train the proposed neural network.

Extensive simulation results in mammographic images have demonstrated that the proposed MMRBF neural network consistently outperforms other RBF algorithms in terms of classification capabilities.

Unfortunately the error is still big in the case of mammographic image analysis, it is due to simple segmentation algorithm used in this paper. The algorithm for segmentation used is based on morphology and thresholding. As future work we will probe with other segmentation algorithm to improve the classification of the regions of interest proposed in this paper.

Finally, in the case of use 256x256 mammographic images and digital signal processors, the processing time can be decreased for real-time applications.

Acknowledgements

The authors thank the National Polytechnic Institute of Mexico for its support.

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