Original Research Article

J. Computing & Int. Systems (2017) 22–25

SACRED HEART RESEARCH PUBLICATIONS

Journal of Computing and Intelligent Systems

Journal homepage: www.shcpub.edu.in

ISSN: 2456 - 9496

Improved Radial Basis Functions using Projection Based Learning Algorithm for Classification Problems

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Received on 16 Jul 2017, Accepted on 25 Jul 2017

Abstract* —The proposed research work combines Projection Based Learning with Radial Basis Function Neural Networks for work out classification. Radial Basis Function Neural Network is combined with Projection Based Learning and same has been proposed as research proposal for solving classification problems. Projection Based Learning-Radial Basis Function constructs good generalization performances of the neural network model by adjusting its weights by means of projection based learning algorithms. The Projection Based Learning algorithm is reduces the learning time, also finds optimum output weight by its energy function. Performance analysis has been evaluated by benchmark datasets for classification problem from machine learning repository of UCI. The performance of the proposed model has produced superior results compared with standard Radial Basis Function for classification.*

Keywords: *Projection Based Learning, Radial Basis Function Neural Networks, Neural Network, Classification, Learning Algorithm.*

1 INTRODUCTION

The Artificial Neural Networks (ANNs) [1] is information processing, inspired by behavior of human biological system, interdisciplinary and it has certain performance characteristics. ANNs has involves in many areas including computer, mathematics, neural system, brain and it is based on the intelligent computation of the computer network imitated by biological neural network that deals with nonlinear problems and huge calculations.

Radial Basis Function (RBF) Neural Network is a three-layer feed-forward neural network, it is connected with a single hidden layer and it can solve any continuous function. RBF neural network is widely used in the traditional classification problems and its architecture is showed in Figure 1. The weights of the RBF [2] [3] is optimized by genetic algorithms for improving its generalization ability. There are two kinds of parameters to be determined in RBF neural network; one is the center and its width of radial basis function, another one is the connection weights between hidden layer and output layer.

Determining the center and width of the hidden layer neurons of the Radial Basis Function [4] is done using a statistical linear regression and its weight modification is done by traditional Gram–Schmidt algorithms.

The classical Gram–Schmidt method is to determine the necessary number of hidden neurons in the hidden layer [5] for the required error in Radial Basis Function. To initialize RBF network parameters, orthogonal least squares algorithm is used with a modified counter propagation network. Build a short-term prediction system based on Echo System Networks [6] to improve prediction accuracy. The weights updating is done by Gram–Schmidt method [7] for standard Radial Basis Function Neural Networks.

By means of literature review, several demeris were found. As a part of it, to update the network weight some papers applied projection based learning. Few research papers that are specific for time series data uses energy function to find optimal weights. Apart from these papers, some reviews on classification uses hinge loss error functions. For the betterment of classification problems, network weights can be enhanced by means of meta-cognitive RBF network(McRBFN) with the learning algorithm Projection Based Learning (PBL). For classification of medical datasets effective performance has been proved by Met-cognitive Interval Type-2 Neuro-Fuzzy Inference System (McIT2FIS). Also the classification performance on various datasets has been proved by modifying McRBFN and PBL. The PBL algorithm improves network accuracy by finding the optimum network weights. Hence, the proposed method is applied for classification problems and the purpose is to simplify the network architecture, improve the training rate and generalization capability of the network.

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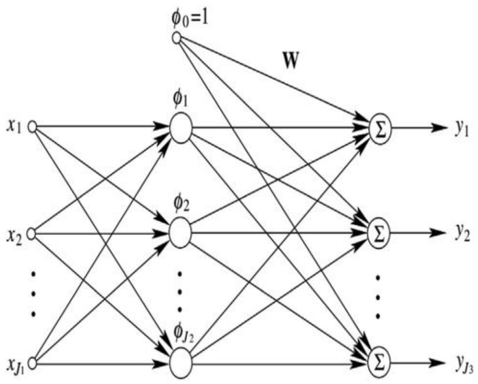

Figure 1 - Architecture of Radial Basis Function Neural Networks

3 METHODOLOGY PROJECTION BASED LEARNING BASED RADIAL BASIS FUNCTIONS NEURAL NETWORKS

The Radial Basis Function Neural Network is a model which performs a nonlinear mapping from input space R^n to the linear output space R^m . R^n is an input vector space that is denoted by x_i (for i=1, 2, 3….n) and R^m is output vector space which is denoted by y (for i=1, 2….m). The j^{th} hidden neuron of the Radial Basis Function, which computes a Gaussian function as below

$$Z_i(x) = \exp(-\frac{\|x-c_j\|}{2\sigma_i^2}) \quad j=1,2,....m \qquad ...(1)$$

Where x is input vector with n dimension, c_j is the center of Gaussian vector of i and σ_i is width of the hidden layer.

The width of the hidden layer is calculated as follows,

$$\sigma_j = \sqrt{\frac{1}{m_j}\sum_{i=1}^{m_j} d^2(c_j - x_i)} \qquad ...(2)$$

The weights updating process done by PBL when a samples is used to update the output layer weight parameter. With the principle of minimizing error function and finding optimal network output weight the learning algorithm PBL executes. A sample entering into the output layer may require update to give optimal weight which can be done by PBL. The considered error function is the Hinge Loss Error Function at output neurons of RBF. An energy function is the sum of squared hinge loss error at output neurons is considered as follows,

$$J_i = \sum_{j=1}^{n} e_j^i, \quad i=1,2,..........,n \qquad ...(3)$$

Where e_j^i is the hinge loss error function that is defined as follows

$$e_j^i = \begin{cases} 0 & if\ \bar{y}_j^i y_j^i \\ \bar{y}_j^i - y_j^i & otherwise \end{cases} \qquad ... (4)$$

When $if\ \bar{y} < 1$, the energy function for i[th] sample becomes as follows,

$$\bar{y}_j^i = \sum_{k=1}^{K} w_{kj} z_k^i \qquad ...(5)$$

$$j_i = \sum_{j=1}^{n} (y_j^i - \bar{y}_j^j)^2 \quad ...(6)$$

Where $\bar{y}_j^j$ is predicted output of the network and y_j^j is actual output of the datasets.

$$\frac{\partial J(w_k^t)}{\partial w(w_{pj})} = \frac{\partial J(w_k^t)}{\partial w(w_{pj})} + \frac{\partial J_t(w_{kl}^t)}{\partial w(w_{pj})} = 0,\ p=1,2,.......K;\ j=1,2....n \qquad ...(7)$$

With respect to zero, equating first partial derivative and re-arranging (7) and get as follow,

$$(A^{t-1} + (h^t)^T W_k^t - (B^{t-1} + (h^t)^T (y^t)^T) = 0 \quad ...(8)$$

By substitute $B^{t-1} = (A^{t-1} + W_k^t A^{t-1} + (h^t)^T) h^t = A^t$ and adding or subtracting the term $(h^t)^T h^t w_K^{t-1}$ on both side reduced to

$$W_k^t = (A^{t-1})(A^t W_k^{t-1} + (h^t)^T (y^t)^T - h^t W_k^{t-1}) \quad ...(9)$$

In finally, the output weight is updates as,

$$W_k^t = W_k^{t-1} + (A^{t-1})(h^t)^T (e^t)^T \quad .... (10)$$

This study utilizes the hinge lose error function [11] for estimating error rate between input and output relationship that minimizes an energy function. For linear problems PBL identifies solution for optimal weights related to the minimum energy function.

4 PERFORMANCE EVALUATION

The proposed model, Projection Based Learning-Radial Basis Function Neural Network is evaluated on familiar benchmark classification datasets and simulation works are conducted with help of MATLAB 2015. Datasets have been collected from UCI machine learning repository [12] and performance of the proposed model has been compared with conventional [13] Radial Basis Function (RBF).

A. Description of Datasets

- Fisher's iris data set contains three different class of Iris flower, 4 types of attributes and which is collected from different 150 samples.
- Wine dataset collected different 178 samples which contains 3 different types of class with 13 features.
- Wisconsin breast cancer dataset collected from various 683 samples with 2 types of class that characterized by 9 features
- Glass, which are collected from of different types of 214 samples and characterized 6 different types of class with 9 types of classes.

B. Performance Measures

The overall classification performance and average classification performance of the proposed model is measured in this paper. The class level performance is measured by the percentage of classification

$$\eta_j = \frac{q_{ij}}{N_j} \times 100\ \% \quad \ldots (11)$$

Where q_{ij} is a total number of its correctly classified example in class j. N_j the total number of examples which is belonging to a class j in the training or testing data set.

The accuracy of the average per-class classification is calculated by

$$\eta_a = \frac{1}{n}\sum_{j=1}^{n} \eta_j \quad \ldots (12)$$

An overall classification accuracy calculated by

$$\eta_0 = \frac{\sum_{j=1}^{n} q_{ij}}{N} \times 100\% \quad \ldots (13)$$

C. Discussions

The class-wise performance measures of average, overall testing efficiencies are discussed below. The performances of the proposed model result are shown in table 1. Table 1 also contains average testing performance on all 4 datasets.

A proposed PBL-RBF algorithm performs well then RBF on all 4 datasets that obtained from the UCI machine learning repository for classification problems. Average per-class classification accuracy, in terms of iris dataset, proposed neural network model, the performance of the classification testing efficiency is improved by 4% than radial basis function. Efficiency of Wine datasets is improved between 2% to 3% than the Radial Basis Functions. 4% of efficiency is improved than RBF for Breast Cancer datasets. Applying in Glass dataset, the efficiency is improved by 2 % than Radial Basis Function. The proposed model is improved in overall classification accuracy also. In terms of iris dataset it is improved by 5%, 2% is improved in both wine and cancer datasets and 1.8% is improved in using Glass datasets than RBF.

Table 1- Performance Analysis of PBL-RBF and RBF for classification

Datasets	PBL-RBF[1]		RBF[2]	
	η_a	η_0	η_a	η_0
Iris	94.75	96.03	90.65	91.09
Wine	98.04	96.39	95.89	94.14
Breast Cancer Wisconsin	85.06	84.06	81.94	82.10
Glass	93.45	92.56	90.56	90.04

[1]Projection Based Learning -Radial Basis Functions
[2]Radial Basis Functions

Figure 2 represents the performance of overall classification accuracy for all the 4 sample datasets. It is demonstrated that proposed method produces superior results than RBF for all datasets.

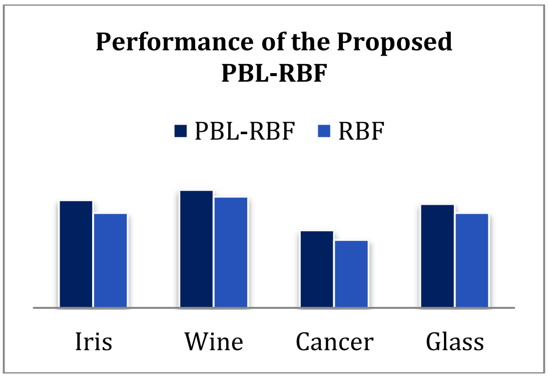

Figure 2- Performance of the Proposed PBL-RBF

5 CONCLUSION

This article projects that the feed forward neural network using Radial Basis Function where output weights are learned by Projection Based Learning algorithm is to reduce the run time with least testing samples and improved generalization performance of neural network architecture. Projection Based learning algorithm accurately estimates its output weight by hinge loss error in order to minimize the misclassification error. The proposed system PBL-RBF has been evaluated with standard datasets and demonstrated which results in 4 % to 5 % improvement on all datasets for class-level as well as average classification accuracy.

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