International Journal of Information Processing, 9(3), 76-91, 2015
ISSN : 0973-8215
IK International Publishing House Pvt. Ltd., New Delhi, India

A Hybrid Fuzzy Firefly Based Evolutionary Radial Basis Functional Network for Classification

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In this paper, a hybrid evolutionary fuzzy firefly based Radial Basis Function (RBF) network hasbeen designed to classify the real world data. The paper is comprised of two stages: first, the Fuzzy c-means (FCM) algorithm is applied with to get effective data points and then those data points have been inputted to the RBFN network for effective classification. The weights of RBF network are updated by using the firefly algorithm. The determination of centres of RBF units strongly affects the performance of a Radial Basis Function network. Various clustering algorithms like K-means and Fuzzy C-means algorithms are widely used to determine the location of centres of RBF units. But the traditional clustering algorithms like Fuzzy c-means algorithm and K-means algorithm are quite sensitive to initialization and they get trapped in the local optima. In order to enhance the performance of RBF network and to avoid the shortcomings of the traditional clustering techniques, a hybrid fuzzy clustering approach integrated with Firefly algorithm has been introduced in this study. The classification accuracy shows the effectiveness of the proposed method when compared with other methods in the literature.

Keywords : Firefly, Fuzzy C-means, PSO, Radial Basis Functional Network.

1. INTRODUCTION

Artificial Neural Networks (ANNs) are computational models that mimic certain processing capabilities of neural cells present in human brain. ANNs have been widely used to solve many real life problems like pattern recognition, function approximation, classification, prediction and data processing. Radial Basis Function Networks (RBFNs) are special type of ANNs introduced by Broomhead and Lowe [1]. Because of their simpler and compact topology, faster learning algorithms, better approximation capabilities, RBFNs have been used in many engineering and scientific problems. Data classification is one of the major applications of the RBFNs.

The learning process of a RBFN includes the optimization of three kinds of parameters: centres and widths of the RBF units as well as the connecting weights between the neurons. Generally a two phase learning strategy is carried out in the optimization of the RBFN parameters. The first phase includes the optimal estimation of the centres and widths of the RBF units by means of various strategies like clustering algorithms, decision trees, self-organizing maps etc. The second phase involves the optimization of connecting weights. This is accomplished by using traditional methods like Gradient Descent algorithms, Singular Value Decomposition (SVD) or Least Mean Squares (LMS) algorithms. During the learning process of a RBFN, the determination of the centres and the widths (kernel parameters) plays an important role in the improvement of the performance of the network. The estimation of the kernel parameters is a crucial and challenging problem, whereas the calculation of the connection weights is a standard process.

Fuzzy cluster analysis seems to be an efficient and promising tool to deal with this prob-

To compare the performance of our proposed method we have considered two other evolutionary methods which are FA-RBFN and PSO-RBFN. In case of FA-RBFN method all the parameters of the RBF network are optimized by means of the firefly algorithm simultaneously. So, a firefly is encoded as a combination of the centers, widths, and weights of the RBF network. In PSO-RBFN, all parameters of the network are optimized by the PSO algorithm. In this method, a particle is represented as a combination of the centers, widths, and weights of the RBF network. Here the objective function for both FA-RBFN and PSO-RBFN is to minimize the MSE of the RBF network.

Tables 7 to Table 11 represent the classification accuracy of the data sets considered using the aforementioned methods. Table 12 compares the classification accuracy of our proposed method with other methods for the considered data sets.
From the tables its clear that our proposed algorithm gives better results in terms of classification as compared to the other classification algorithms FA-RBFN and PSO- RBFN for the data sets considered. It can also be observed that our proposed method provides better results when compared with other existing methods from the described literatures.

6. CONCLUSIONS

Now-a-days, researchers in various fields have been attracted towards the neural network research due to their vast applicability in diverse areas. In this study, an evolutionary learning strategy for constructing a data classifier using the radial basis function network, FCM and firefly algorithm have been proposed. The determination of kernel parameters in the RBFN has great significance in the performance of the network. A novel hybrid fuzzy clustering approach based on firefly algorithm was used to estimate the centres of the RBF units effectively and clustered the hidden units of the network efficiently. The connecting weights were also optimized by the help of firefly algorithm. To validate the performance of our proposed methodology many real world datasets are considered and the classification results revealed the superiority of the proposed method over the existing methods. From the comparative analysis and the obtained results indicate that the learning of RBFN by the proposed fuzzy method is quite promising and can be efficiently used in data classification task. In the near future, some other evolutionary or nature inspired optimizations techniques may be applied for the more accurate kernel parameter estimation of RBF network. Also, another direction of the work is the construction of new neurons or fuzzy neural architecture for various real world applications.

REFERENCES

1. D S Broom head, Lowe and David. Radial Basis Functions, Multi-Variable Functional Interpolation and Adaptive Networks, *(Technical Report) RSRE,* pages 41–48, 1988.
2. A D Niros and G E Tsekouras. A Novel Training Algorithm for RBF Neural Network using a Hybrid Fuzzy Clustering Approach, *Fuzzy Sets and Systems,* 193:62-84, 2012.
3. S N Qasem and S M Shamsuddin. Radial basis function network based on time variant multi-objective particle swarm optimization for medical diseases diagnosis, *Applied Soft Computing,* 11:1427-1438, 2011.
4. J Yua and H Duan. Artificial Bee Colony Approach to Information Granulation-Based Fuzzy Radial Basis Function Neural Networks for Image Fusion, *Optik,* 124:3103-3111, 2013.
5. S K Oh, et al.,. Polynomial-Based Radial Basis Function Neural Networks (P-RBF NN) Realized with the Aid of Particle Swarm Optimization, *Fuzzy Sets and Systems,* 163:54-77, 2011.
6. G G Looney. Fuzzy Connectivity Clustering with Radial Basis Kernel Functions, *Fuzzy Sets and Systems,* 160:1868-1885, 2009.
7. Whei-Min Lin , Hong-Jey Gow and Ming-Tang Tsai. An Enhanced Radial Basis Function Network for Short-Term Electricity Price Forecasting, *Applied Energy,* 87:3226-3234, 2010.
8. Jeen Lin and Ruey-Jing Lian. Hybrid Self-Organizing Fuzzy and Radial Basis-Function Neural- Network Controller for Gas-Assisted Injection Molding Combination Systems,

Table 7
Comparison of Classification Accuracy for Iris Dataset

PCC	Proposed Method	FA-RBFN	PSO-RBFN
Max	100	97.66	97.33
Min	95.33	93.33	93.66
Mean	99.33	95.33	94.66

Table 8
Comparison of Classification Accuracy for Wine Dataset

PCC	Proposed Method	FA-RBFN	PSO-RBFN
Max	100	98.85	98.57
Min	100	95.71	95.71
Mean	100	97.42	96.85

Table 9
Comparison of Classification Accuracy for WDBC Dataset

PCC	Proposed Method	FA-RBFN	PSO-RBFN
Max	99.82	98.23	97.33
Min	95.57	96.01	95.84
Mean	98.48	97.34	96.99

Table 10
Comparison of Classification Accuracy for Breast Cancer Dataset

PCC	Proposed Method	FA-RBFN	PSO-RBFN
Max	100	100	100
Min	100	95.68	95.03
Mean	100	97.76	97.19

Table 11
Comparison of Classification Accuracy for Diabetes Dataset

PCC	Proposed Method	FA-RBFN	PSO-RBFN
Max	78.62	72.02	71.04
Min	73.01	68.59	68.59
Mean	77.98	69.01	68.75

Mechatronics 20:698-711, 2010.

9. Seok-Beom Roh, Su-ChongJoo, WitoldPedrycz and Sung-KwunOh. The Development of Fuzzy Radial Basis Function Neural Networks Based on the Concept of Information Ambiguity, *Neurocomputing,* 73:2464-2477, 2010.
10. Sultan Noman Qasem and Siti Mariyam Shamsuddin. Memetic Elitist Pareto Differential Evolution Algorithm Based Radial Basis Function Networks for Classification Problems, *Ap-*

Table 12
Comparison of Classification Accuracy of the Proposed Method with other Methods

Methods	Iris	Wine	WDBC	Breast Cancer	Diabetes
Proposed method	99.33	100	98.48	100	77.98
MLP-Ann	100	98.67	97.07	94.75	70.84
MultiBoost	97.37	82.33	94.41	94.86	72.92
NBTree	97.37	97.78	94.29	92.31	74.48
BayesNet	97.37	100	95.81	96.58	74.48
Bagging	99.74	97.34	94.41	94.86	72.92

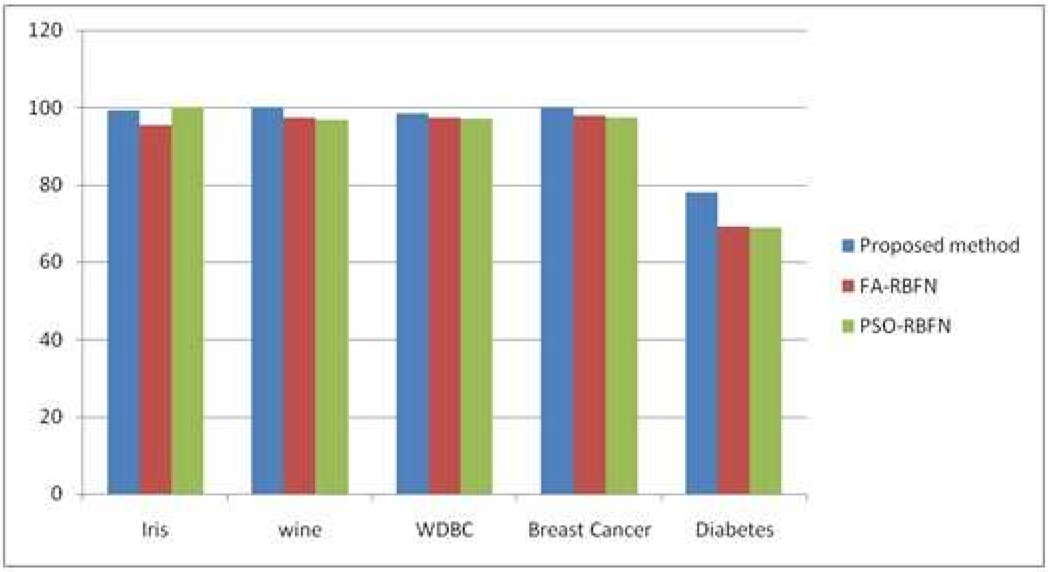

Figure 3. Comparison of Classification Accuracy

plied Soft Computing 11:5565-5581, 2011.

11. Francisco Ferna ndez-Navarro, Ce sar Herva s-Mart nez, JavierSanchez-Monedero and Pedro AntonioGutie rrez. MELM-GRBF: A Modified Version of the Extreme Learning Machine for Generalized Radial Basis Function Neural Networks, *Neurocomputing,* 74:2502-2510, 2011.
12. Yu-Yi Fu, Chia-Ju Wu, Chia-Nan Ko and Jin-Tsong Jeng. Radial Basis Function Networks with Hybrid Learning for System Identification with Outliers, *Applied Soft Computing,*11:3083-3092, 2011.
13. Wei Shen , Xiaopen Guo , Chao Wu and Desheng Wu. Forecasting Stock Indices using Radial Basis Function Neural Networks Optimized by Artificial Fish Swarm Algorithm, *Knowledge-Based Systems,* 24:378-385, 2011.
14. Xiao-hui Tan, Wei-hua Bi, Xiao-liang Hou and Wei Wang. Reliability Analysis Using Radial Basis Function Networks and Support Vector Machines, *Computers and Geotechnics,* 38:178-186, 2011.
15. Di Wang, Xiao-JunZeng and John A Keane. A Clustering Algorithm for Radial Basis Function Neural Network Initialization, *Neurocomputing,* 77:144-155, 2012.
16. Francisco Ferna ndez-Navarro, Ce sar Herva s-Mart nez, PedroA.Gutie rrez, JoseM.Pen a Barraga and Francisca Lo pez-Granados. Parameter Estimation of Q-Gaussian Radial Basis Functions Neural Networks with a Hybrid Algorithm for Binary Classification, *Neurocomputing,* 75:123–134, 2012.

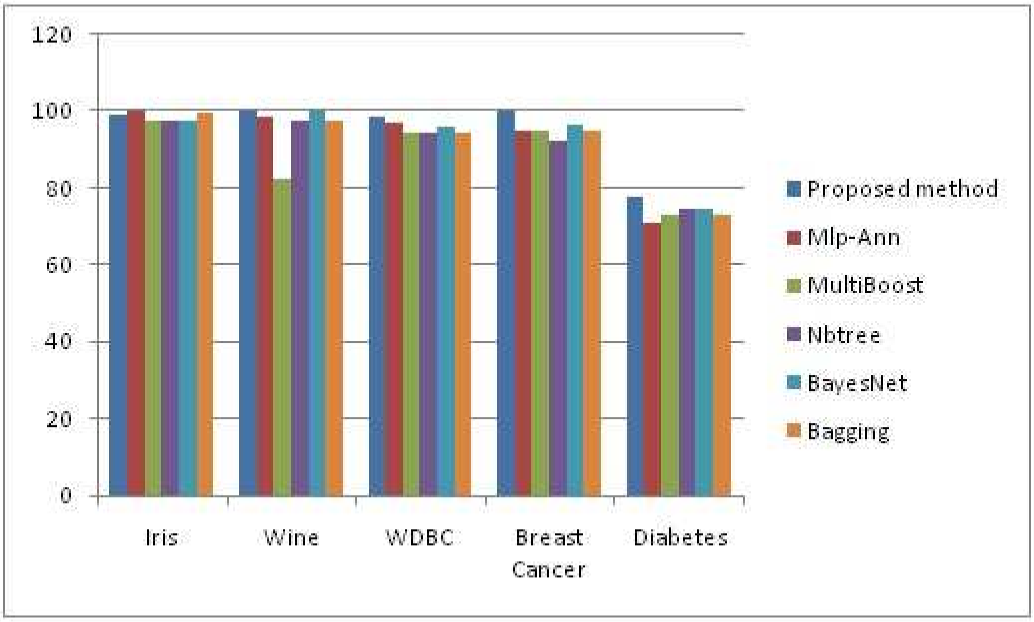

Figure 4. Comparison of Classification Accuracy of Our Method with other Work

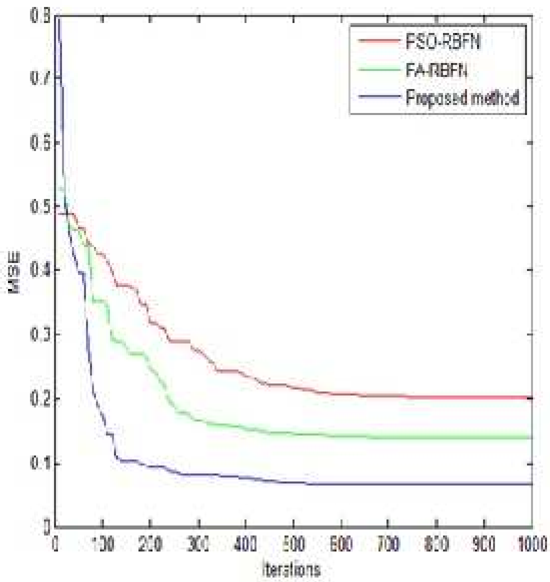

Figure 5. Comparison of Convergence of Different Methods for Iris Dataset

17. Guojiang Xiong, Dongyuan Shi, Jinfu Chen, Lin Zhu and Xianzhong Duan. Divisional Fault Diagnosis of Large-Scale Power Systems Based on Radial Basis Function Neural Network and Fuzzy Integral, *Electric Power Systems Re-*

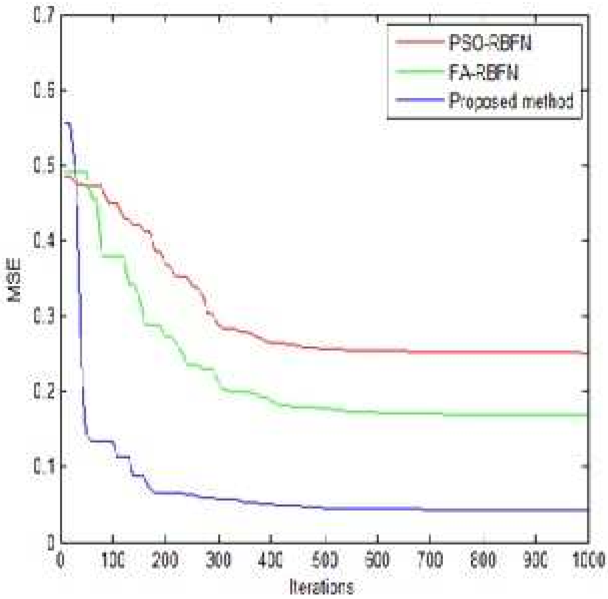

Figure 6. Comparison of Convergence of Different Methods for Wine Dataset

search, 105:9–19, 2013.

18. Afshin Mehrsai, Hamid-RezaKarimi, Klaus-DieterThoben and BerndScholz-Reiter. Application of Learning Pallets for Real-Time Scheduling by the use of Radial Basis Function Network, *Neurocomputing,* 101:8293, 2013.
19. M D Prez-Godoy, Antonio J Rivera, C J Carmona and M J del Jesus. Training Algorithms for Radial Basis Function Networks to Tackle Learning Processes with Imbalanced Data-Sets, *Applied Soft Computing,* 25:26–39, 2014.
20. Wei Huang, Sung-Kwun Ohc and Witold Pedrycz. Design of Hybrid Radial Basis Function Neural Networks (HRBFNNs) Realized with the Aid of Hybridization of Fuzzy Clustering Method (FCM) and Polynomial Neural Networks (PNNs), *Neural Networks,* 60:166–181, 2014.
21. Jinna Lu, Hongping Hu and Yanping Bai. Generalized Radial Basis Function Neural Network Based on an Improved Dynamic Particle Swarm Optimization and AdaBoost Algorithm, *Neurocomputing,* 152:305–315, 2015.
22. Q PH a, H Wahid, H Duc and M Azzi. Enhanced Radial Basis Function Neural Networks for Ozone Level Estimation, *Neurocomputing,* 155:62–70,2015.
23. Dino Kosic. Fast Clustered Radial Basis Function Network as an adaptive predictive controller, *Neural Networks,* 63:79–86, 2015.
24. D K Siong Tok, Ding-LiYu, Christian Mathews, Dong-Ya Zhao and Quan-Min Zhu. Adaptive Structure Radial Basis Function Network Model for Processes with Operating Region Migration, *Neurocomputing,* 155:186–193, 2015.
25. X S Yang. Firefly Algorithms for Multimodal Optimization, Stochastic Algorithms:Foundations and Application, *SAGA Lecture Notes in Computer Sciences,* 5792:169–178, 2009.
26. X S Yang. Nature-Inspired Metaheuristic Algorithms, *Luniver Press,* 2008.
27. J Nayak, B Naik and H S Behera. Fuzzy C-Means (FCM) Clustering Algorithm: A Decade Review from 2000 to 2014, *In Computational Intelligence in Data Mining, Springer India* 2:133–149, 2015.
28. J Nayak, M Nanda, K Nayak, B Naik and H S Behera. An Improved Firefly Fuzzy C-Means (FAFCM) Algorithm for Clustering Real World Data Sets, *In Advanced Comput-*

ing, Networking and Informatics Springer International Publishing, 1:339–348, 2014.
29. GT Chandra, Sekhar et al. Load Frequency Control of Power System Under Deregulated Environment Using Optimal Firefly Algorithm, *International Journal of Electrical Power and Energy Systems*, 74:195–211, 2016(In Press).
30. Kennedy J and Eberhart R. Particle Swarm Optimization *Proceedings of the 1995 IEEE International Conference on Neural Networks,* 4:1942–1948, 1995.
31. J Nayak, B Naik, H S Behera and A Abraham. Particle Swarm Optimization Based Higher Order Neural Network for Classification, *In Computational Intelligence in Data Mining, Springer India*, 1:401–414, 2015.
32. Bache K and Lichman M. UCI Machine Learning Repository[http://archive.ics.uci.edu/ml], Irvine, CA: University of California, School of Information and Computer Science, 2013.

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