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An experimental learning of Fuzzy Neural Classifiers

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Abstract

In this paper we have compared the performance of training algorithms of fuzzy neural classifiers namely EFHLSNN and EFHSNN on three different multivariate data sets. Multivariate dataset play very important role in Multivariate statistics, which is a form of statistics Analysis. The classifiers that we have selected are purely used for pattern classification and clustering problems. Experimental results show that the use of the EFHSNN and EFHLSNN classifier results in better learning, training and recall time, and equivalent percentage recognition on multivariate dataset.

1. Introduction

In recent times the number of fuzzy neural network paradigms has augmented significantly. This development led us to the question of which is the "best" fuzzy neural network for solving a pattern classification task. In developing algorithms, it is important to know the computational properties of available algorithms. This calls for an experimental comparison of the fuzzy neural algorithms. Also the datasets should comprise different properties posing different challenges to the networks.

In the original paper [1, 2], we have presented a comparison of EFHSNN and EFHLSNN algorithms using fingerprint database generated by POLY U HRF. And the evaluation of these algorithms with other dataset is necessary, because only then the correct results will be known. In this paper we apply the same fuzzy neural algorithms to three multivariate [3] data sets. Then the correct or theoretically best results will be known, and it is possible to compare the algorithms only mutually or with respect to their performance in the application at hand.

2. EFHSNN algorithm

The EFHSNN classifier which is an extension of Fuzzy Hypersphere Neural Network (FHSNN) proposed by Kulkarni *et. al.,* [84, 85] to the problem of fingerprint recognition based on FingerCode feature data, which utilizes fuzzy sets as pattern classes in which each fuzzy set is an union of fuzzy set hyperspheres. The fuzzy set hypersphere is an *n*-dimensional hypersphere defined by a center point and radius, which is characterized by hypersphere membership function. The supervised EFHSNN learning algorithm for creating fuzzy hyperspheres in hyperspace consists of three steps 1) Creation of hyperspheres, 2) Overlap test and 3) Removing overlap.

The EFHSNN consists of four layers as shown in Figure 1. The first, second, third and fourth layer is denoted as F_R, F_M, F_N and F_O respectively. The F_R layer accepts an input pattern and consists of *n*-processing elements, one for each dimension of the pattern. The F_M layer consists of q processing nodes that are constructed during training and each node represents fuzzy set hypersphere. The fuzzy set hypersphere is an *n*-dimensional hypersphere defined by a center point and radius, which is characterized by hypersphere membership function.

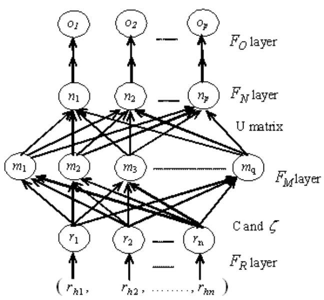

Figure 1: Topology of Extended Fuzzy Hypersphere Neural Network

3. EFHLSNN algorithm

The EFHLSNN algorithm is an extension of Fuzzy Hyperline Segment Neural Network (FHLSNN). The EFHLSNN utilizes fuzzy sets as pattern classes in which each fuzzy set is a union of fuzzy set hyperline segments. The fuzzy set hyperline segment is an *n*-dimensional hyperline segment defined by two end points with a corresponding membership function. The performance of EFHLSNN is verified using POLYU HRF fingerprint database. The EFHLSNN is found

superior compared to FHLSNN, FMN and GFMN in generalization, training and recall time.
The architecture of EFHLSNN consists of four layers as shown in figure 2. In this architecture first, second, third and fourth layer is denoted as F_R, F_E, F_D and F_C, respectively. The F_R layer accepts an input pattern and consists of n processing elements, one for each dimension of the pattern. The F_E layer consists of m processing nodes that are constructed during training. There are two connections from each F_R to F_E node; one connection represents one end point for that dimension and the other connection represents another end point of that dimension, for a particular hyperline segment. One end point of fuzzy hyperline segment is stored in matrix V and the other end point is stored in matrix W.

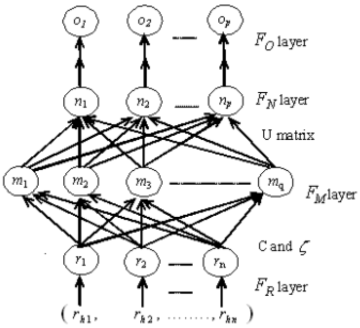

Figure 2: Extended Fuzzy hyperline segment neural network.

4. Experimental results using multivariate dataset

Multivariate dataset play very important role in Multivariate statistics, which is a form of statistics Analysis. It encompassing the simultaneous observation and analysis of more than one statistical variable. One of the applications of multivariate statistics is multivariate analysis.

I. Iris Flower dataset

The Iris flower data set or Fisher's Iris data set is a multivariate data set introduced by Sir Ronald Aylmer Fisher (1936) as an example of discriminant analysis [1]. The dataset consists of 50 samples from each of three species of Iris flowers (Iris setosa, Iris virginica and Iris versicolor). Four features were measured from each sample, they are the length and the width of sepal and petal, in centimeters. Based on the combination of the four features, Fisher developed a linear discriminant model to distinguish the species from each other.

We have compared EFHSNN and EFHLSNN algorithm with this dataset; the experimental results in terms of Average training time, average recall time and recognition rate are obtained are depicted in Table 1. The experimental results shows that the EFHLSNN algorithm takes less training and recall time as compared with EFHSNN algorithm with equivalent recognition rate of 96.66 %, in which among 150 total patterns 145 patterns are correctly classified using both the algorithms.

Table 1: Timing Analysis of algorithms with Iris dataset

Classifier	Average Training Time (Seconds)	Average Recall Time (Seconds)	Recognition Rate
EFHSNN	0.860723	5.020086	96.66 %
EFHLSNN	0.2011	0.735871	96.66 %

II. Wine dataset

We evaluated the EFHSNN and EFHLSNN algorithm on multivariate wine data set taken from UCI machine learning repository (6) for testing the efficiency of these algorithms. The data is the result of a chemical analysis of wines grown in a region in Italy but derived from three different cultivars. There are three classes. The dataset consists of 178 examples each with 13 continuous attributes. The data set contains distribution 59 examples of class 1, 71 examples for class 2 and 48 examples for class 3.

The experimental results in terms of Average training time, average recall time and recognition rate are obtained are depicted in Table 2. The experimental results shows that the EFHLSNN algorithm takes less training and recall time as compared with EFHSNN algorithm with equivalent recognition rate of 100%, in which among 178 total patterns are correctly classified into three classes using both the algorithms.

Table 2: Timing Analysis of algorithms with Wine dataset

Classifier	Average Training Time (Sec.)	Average Recall Time (Sec.)	Recognition Rate
EFHSNN	1.018584	4.381980	100 %
EFHLSNN	0.2705	1.057828	100

III. Ionosphere dataset

The Johns Hopkins University Ionosphere database is taken from the UCI Repository of Machine Learning Databases donated by Vince Sigillito in 1989. This dataset has been used in the past for classification of radar returns from the ionosphere by Sigillito. This radar data was collected by a system which consists of phased array of 16 high-frequency antennas together with a total transmitted power on the order of 6.4 kilowatts.

The free electrons in the ionosphere were the target. Those that show the evidence of some structure in the ionosphere are Good radar returns while bad returns are those that do not. There signals were passed through the ionosphere, the received signals were processed with the use of an auto-correlation function with two arguments which are the time of a pulse and the pulse number. Received signals were processed using an autocorrelation function whose arguments are the time of a pulse and the pulse number. There were 17 pulse numbers for the Goose Bay system. Instances in this databse are described by 2 attributes per pulse number, corresponding to the complex values returned by the function resulting from the complex electromagnetic signal.

The experimental results in terms of Average training time, average recall time and recognition rate are obtained are depicted in Table 3. The experimental results shows that the EFHLSNN algorithm takes less training and recall time as compared with EFHSNN algorithm with equivalent recognition rate of 100%.

Table 5: Timing Analysis of algorithms with Crab dataset

Classifier	Average Training Time (Seconds)	Average Recall Time (Seconds)	Recognition Rate
EFHSNN	1.521684	5.275599	100
EFHLSNN	0.4056	1.351183	100

5. Conclusions

From the experiments made for revealing various aspects of EFHSNN and EFHLSNN algorithms, the following general conclusions can be made. The first conclusion is the stability of EFHSNN and EFHLSNN algorithms. This is a good characteristic encouraging the use of these algorithms for a general data analysis tool. Second conclusion is that the EFHLSNN algorithm gives better results as compared to EFHSNN algorithm in terms of training and recall time. Third conclusion is that in this paper we have applied this dataset for multivariate datasets. In Future

it would be interesting to implement this algorithm for other areas like Aviation marketing, Stock Marketing, Market Trading, Bone Cancer Detection and also in Banking Sector.

References

[1] M. H. Kondekar, U. V. Kulkarni & S. S. Chowhan, “Fingerprint Recognition Using Extended Fuzzy Hypersphere Neural Network,” *Journal Of Computing*, Volume 3, Issue 4, pp: 101-105, April 2011, ISSN 2151-9617, USA.

[2] M. H. Kondekar, U. V. Kulkarni, & B. B. M. Krishna Kanth, “Extended Fuzzy Hyperline Segment Neural Network for Fingerprint Recognition,” *International Journal of Biometrics and Bioinformatics (IJBB)*, Volume 5, Issue 3, pp. 162-171, July-August 2011, Malaysia.

[3] Schervish Mark J. ,"A Review of Multivariate Analysis," *Statistical Science* 2 (4):396–413.doi:10.1214/ss/1177013111. ISSN 0883-237. JSTOR 2245530,(November 1987).

[4] U.V. Kulkarni and T.R. Sontakke, “Fuzzy Hypersphere Neural Network Classifier,”

Proceedings of 10th International IEEE Conference on Fuzzy Systems, University of Melbourne, Australia, December 2001, pp. 1559-1562.

[5] U.V. Kulkarni, T.R. Sontakke and G. D. Randale, "Fuzzy Hyperline Segment Neural Network for Rotation Invariant Handwritten Character Recognition," *Neural Networks*, *Proceedings. IJCNN '01. International Joint Conference on Neural Network*, Washington, DC, USA, 2001, pp. 2918 - 2923 vol.4.