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Lung Cancer Classification using Fuzzy Hyperline Segment Neural Network (FHLSNN)

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ABSTRACT
Pattern recognition has become more and more popular as it induces attractive attention coming from wider areas. This paper describes Fuzzy Hyperline Segment Neural Network (FHLSNN) with its learning algorithm. The FHLSNN is a supervised learning neural network classifier that utilizes fuzzy sets as pattern classes. Here each fuzzy set is a union of fuzzy set hyperline segments. The performance of Fuzzy Hyperline Segment Neural Network (FHLSNN) [1] is compared with other fuzzy neural networks like Fuzzy Hypersphere Neural Network (FHSNN) [2], proposed by Kulkarni et. al..

Key words : Fuzzy Hypersphere Neural Network (FHSNN), Fuzzy Hyperline Segment Neural Network (FHLSNN), Fuzzy Neural Network (FNN), Hyperline Segment (HLS).

1. INTRODUCTION

The fuzzy neural networks are an example of a hybrid approach, being widely used in pattern recognition applications. It combines the strengths of both neural networks and fuzzy logic, making it a powerful tool. Supervised and unsupervised are the two main training strategies used in fuzzy neural networks. Both techniques are used in difference scenarios. Supervised learning is a method in which patterns are trained under supervision using class labels. This method is used in pattern classification problem. In unsupervised leaning, patterns are unlabeled. This method is used in clustering problem. The clusters of patterns are formed on the basis of similarity measure.

Chiang and Gader [4] have proposed two hybrid fuzzy neural systems for handwritten word recognition. Joshi et.al. [5] and Meneganti et.al. [6] have worked on the problems of pattern classification and recognition. Kwan and Cai [7] have proposed four-layer feed forward unsupervised fuzzy neural network. Patrick Simpson [8] proposed supervised fuzzy min max neural network [FMN] that utilizes fuzzy sets as pattern classes. Pedrycz and Waletzky [9] presented fuzzy clustering with partial supervision and proved that small percentage of labeled patterns can improve result of clustering. Gabrys and Bargiela [10] have proposed general fuzzy min-max neural network (GFMM) for clustering and classification with fusion of supervised and unsupervised learning.

1.1 Topology of FHLSNN

The architecture of FHLSNN consists of four layers as shown in Fig.1. In this architecture first, second, third and fourth layer is denoted as , , and , respectively. The layer accepts an input pattern and consists of n processing elements, one for each dimension of the pattern. The layer consists of m processing nodes that are constructed during training. There are two connections from each to node; one connection represents one end point for that dimension and the other connection represents another end point of that dimension, for a particular HLS as shown in Fig.1. Matrix V and Matrix W are used to store end points of fuzzy HLSs.

Each node of D_C and D_D layer represents a class.

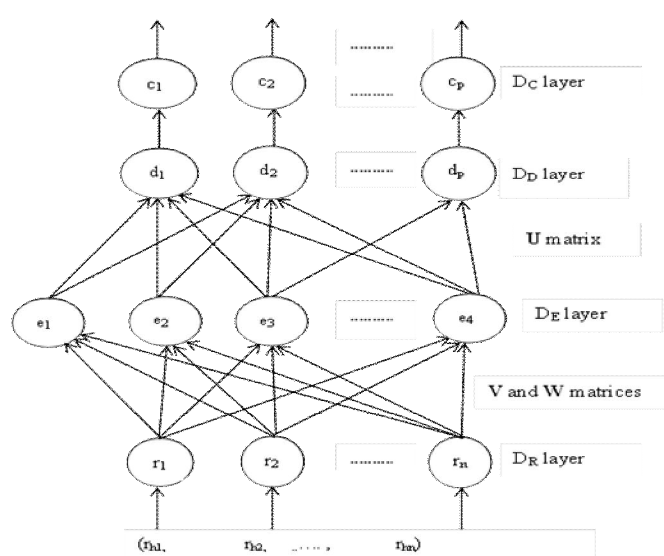

Figure 1 : Fuzzy hyperline segment neural network

The weights assigned between D_E and D_D layers are stored in the **U** matrix. Let $R_h = (r_{h1}, r_{h2}, \ldots, r_{hn})$ is the h^{th} input pattern, $V_j = (v_{j1}, v_{j2}, \ldots, v_{jn})$ and $W_j = (w_{j1}, w_{j2}, \ldots, w_{jn})$ are two end points of the HLS e_j. Then the fuzzy HLS membership function of j^{th} F_E node is defined as

$$e_j(R_h, V_j, W_j) = 1 - f(x, \gamma_1, l), \quad (1)$$

In which $x = l_1 + l_2$, and the distances l_1, l_2 and l are defined as,

$$l_1 = \left[\sum_{i=1}^{n}(w_{ji} - r_{hi})^2\right]^{1/2}, \quad (2)$$

$$l_2 = \left[\sum_{i=1}^{n}(v_{ji} - r_{hi})^2\right]^{1/2}, \quad (3)$$

$$l = \left[\sum_{i=1}^{n}(w_{ji} - v_{ji})^2\right]^{1/2}, \quad (4)$$

and *f(.)* is a three-parameter ramp threshold function defined as,

$$f(x, \gamma_1, l) = 0 \qquad if\ x = l\ \text{otherwise}$$

$$f(x, \gamma_1, l) = \begin{cases} x\gamma_1, & if\ 0 \le x\gamma_1 \le 1 \\ 1, & if\ x\gamma_1 > 1. \end{cases} \quad (5)$$

The parameter γ_1 is used to see how fast the membership value decreases when the distance between R_h and e_j increases. Each node of D_C and D_D layer represents a class. The D_D layer gives soft decision and output of k^{th} D_D node represents the degree to which the input pattern belongs to class d_k. The weights assigned to the connections between D_E and D_D layers are binary values and stored in matrix U and the values assigned to these connections are defined as

$$u_{jk} = \begin{cases} 1, & \text{if } b_j \text{ is the HLS of class } n_k \\ 0, & \text{otherwise} \end{cases}$$

for $k=1,2,\ldots,p$ and $j=1,2,\ldots,q$. (6)

The transfer function of each D_D node performs the union of same class hyperline segment fuzzy values, which is given as,

$$d_k = \max_{j=1}^{m} e_j u_{jk} \text{ for } k = 1, 2, \ldots, p \quad (7)$$

Each D_C node delivers nonfuzzy output described as,

$$c_k = \begin{cases} 1, & if\ d_k = T \\ 0, & if\ d_k < T \end{cases} \quad (8)$$

where T=max(d_k), for all k= 1 to p.

The learning algorithm consists of three steps, creation of HLSs, intersection test and removal of intersection.

2. Experimental Results

The fuzzy hyperline segment neural network is tested on the public Standard Digital Image Database, JSRT [11]. The data samples in JSRT are divided into five subsets according to the subtlety of nodule. These images contain nodules within the range 5-60 mm. Before passing these images to the classifier, pre-processing including normalization of size, filtering to enhance the contrast is done. Table 1 shows the performance of FHSNN and FHLSNN in terms of % recognition rate, number of hyperspheres/hyperlines and the λ value. λ represents the maximum radius limit of the hypersphere of fully trained neural network.

Table 1: Comparative performance of FHSNN and FHLSNN on JSRT database

Classifier	λ Value	No. of HS/HL	Recognition rate (%)
FHSNN	0.051	75	85.53
FHLSNN	0.51	71	87.66

Out of 92 samples, 80 samples are used for training and remaining 22 are used for testing purpose. The FHLSNN gives better recognition rate as compared to FHSNN. Also the number of hyperlines created is less and hence the training time and recall time in seconds is less than FHSNN.

Table 2. Training time and recall time of FHSNN and FHLSNN

Classifier	Training time in Seconds	Recall time in Seconds
FHSNN	5.13	2.39
FHLSNN	4.02	3.82

3. Conclusion

Two different fuzzy neural classification algorithms have been investigated in this work, which use fuzzy sets as pattern classes in the hyperspace. Here performance of FHLSNN is better than FHSNN in terms of recognition rate, training time and recall time.

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