Iris Recognition Using Fuzzy Min-Max Neural Network

S.S.Chowhan, *Member, IACSIT,* and G. N. Shinde

***Abstract*—Iris is one of the best biometric features for security applications. This paper focuses on the iris recognition and classification system and its performance in biometric identification system. The steps of iris recognition include image normalization, feature extraction and classifier. This work is an application of Patrick Simpson's fuzzy min-max neural network (FMN) Classification. Fuzzy min-max classification neural networks are built using hyperbox fuzzy sets. We performed comparative studies of different similarity measures applied to various classifiers. The feasibility of the FMN Classification Algorithm has been successfully evaluated on CASIA database with 756 images and found superior in terms of generalization and training time with equivalent testing time.**

***Index Terms*—Biometrics, Feature extraction, Fuzzy Min-max neural network.**

I. Introduction

In the past decade, fuzzy systems have replaced conventional technologies in many scientific applications and engineering systems, especially in control systems and pattern recognition. They can provide decision-support and expert systems with powerful reasoning capabilities bound by a minimum of rules [1]. In practice FNN's have found useful in many application fields, for instance, system modelling, system reliability analysis, pattern recognition, and knowledge engineering and so on. Based on fuzziness involved in FNN's developed since the late of 1980s [2].There are two main training schemes employed by fuzzy neural networks; In supervised learning, class labels are provided with input patterns and the decision boundary between classes that minimizes misclassification is achieved. It is often referred as pattern classification problem.

In unsupervised learning, training patterns are unlabeled and clusters of the patterns are formed with a suitable similarity measure, which is referred as clustering problem [3].The FNN models have attracted many scholars' attention. A lot of new concepts, such as innovative architecture and training rules and models about FNN's have been proposed. Hung-Hsu Tsai and Pao-Ta Yu had proposed four layer FNN for robust learning of an FNN [4]. Kwan and Cai proposed the four layer feedforward neural network When an input pattern is provided the network first fuzzifies this pattern and then computes the similarities of this pattern to all of the learned patterns. The network then reaches a conclusion by selecting the learned pattern with the highest similarity and gives a nonfuzzy output[6].

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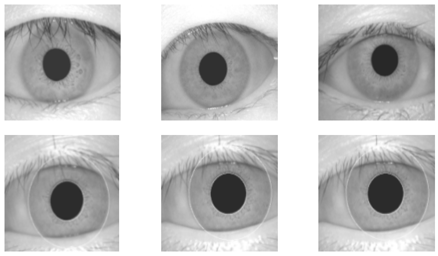

Fig. 1. Samples of Iris images with occlusion and inner and outer boundaries detected

Rui-Ping Li et al had proposed A Fuzzy Neural Network for Pattern Classification and Feature Selection which enables the classification of patterns and the selection of features and two types of learning algorithm was introduced, i.e., unsupervised learning for memory connection and supervised learning for weight connection [7]. Ability of the feature-weighted detector (FWD) network is to classify pattern and select feature.

Li Jinling had proposed Fuzzy neural network based on rectangle functions and its application Fuzzy neural network (FNN) based on rectangle functions is constructed by partitioning input space into many disjoint hyper-cubes with the same size[8]. This model is constant in each of the hyper-cubes. If and only if an input pattern drops into a hyper-cube would the corresponding pattern be memorized through coding. The FMMIS algorithm uses seed pixels to grow hyperboxes, and a criterion of homogeneity for controlling the size of these hyperboxes. If the homogeneity criterion is satisfied, a hyperbox could be expanded from a given size to any other size by including a new seed pixel which was used faster segmentation [10]. Juan Wachs et al had focused on automated method of segmentation of faces in color images using fuzzy min-max neural network which automatically segments the skin colors of the face in a Hue Saturation Value color model [11]. Cheng, H.D. Cui, M. had proposed Mass lesion detection with a fuzzy neural network approach to detect malignant mass lesions on mammograms [12]. Suliman M Mohamed et al had used fuzzy neural network for Automatic Fingerprint Classification this classifier was trained and tested on 4000 images in NIST-4 database [13].

II. Features of Fuzzy Set and Membership Function

Fuzzy sets were introduced by Zadeh as a means of representing and manipulating data that were not precise, but rather fuzzy [14]. Zadeh's extension of set theory provided a mechanism for representing linguistic constructs such as "little more"," very tall", "very far" and it gave pattern classification and control engineers the ability to measure the degree to which a pattern was present or a situation was occurring. The values assigned to the elements of the universal set fall within a specified range and indicate the membership grade of these elements in the set. Larger values denote higher degrees of set membership [9]. Such a function is called membership function, and the set defined by it a fuzzy set. The most common notation are employed to denote the membership functions of a fuzzy set A is.

$$A=\{x,\mu_A(x)\mid x\in X\} \tag{1}$$

Each fuzzy set is completely and uniquely defined by one particular membership function. The membership value $\mu_A(x)$ describes the degree to which the element belongs to the set A, where $\mu_A(x)=0$ represents lowest membership and $\mu_A(x)=1$ represents highest membership.

In pattern classification using fuzzy sets, class fuzzy sets are created with the nature of input patterns applied to the fuzzy-neural networks. This is the training process. In recall phase the membership value of input pattern is calculated in all class fuzzy sets and the class label of a fuzzy set is given to the input pattern in which it acquires highest membership.

A. Normal Fuzzy set

A fuzzy set defined by its membership function must be a normal fuzzy set. A normal fuzzy set is defined as a set in which at least one element from the universe has membership value to be highest is called as normal when $h(A)=1$. Fig. 2 shows a normal fuzzy set, it is called subnormal when $h(A)<1$, that is.

$$h(A)=\sup_{x\in X} A(x) \tag{2}$$

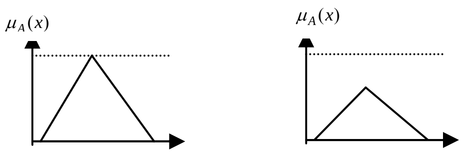

Fig. 2. Normal fuzzy set and subnormal fuzzy set

B. Fuzzy set operations

The three basic operations on classical sets are union, intersection and complement can be generalized in more than one way [10] which are usually referred to as standard fuzzy set operations, has special significance in fuzzy set theory. These operations are defined as follows.Union of two fuzzy sets A and B is a fuzzy set C is defined as

$$\mu_C(x)=\mu_A(x)\vee\mu_B(x)=\max[\mu_A(x),\mu_B(x)];x\in X \tag{3}$$

Intersection of two fuzzy sets A and B is a fuzzy set C is defined as

$$\mu_C(x)=\mu_A(x)\wedge\mu_B(x)=\min[\mu_A(x),\mu_B(x)];x\in X \tag{4}$$

Absolute and relative complements are defined as

$$\mu_A(x)=1-\mu_A(x)\ \textit{for all } x\in X \tag{5}$$

A relative complement of A with respect to B denoted by B – A is defined by $\mu_A(x)=\mu_B(x)-\mu_A(x)$.

III. Topology of Fuzzy Min-Max Neural Network

The fuzzy min-max neural network consists of three-layer as shown in the figure 2. The input layer $F_A=(a_1,a_2......a_n)$ has n processing elements, one for each of the n dimensions of the input pattern A_h. There are two sets of connections between each input node and each of the m hyper box fuzzy set nodes found in the layer $F_B=(b_1,b_2.......b_n)$. These dual connections are adjusted using the fuzzy min-max classification learning algorithm. There are two sets of connections that emanate from F_A and neighbor of the j^{th} F_B node-the min vector V_j, and the max vector W_j. The connections between the F_B nodes and the p output nodes $F_C=(c_1,c_2.......c_p)$ are binary valued and are determined as each F_B node is added during learning. Each F_C node represents a pattern class [5].

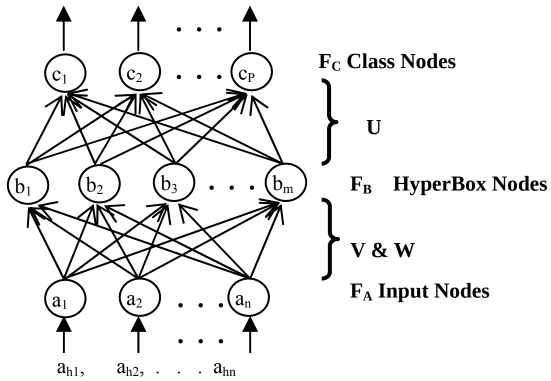

Fig. 3. Topology of fuzzy min-max neural network

Let the j^{th} hyper box fuzzy set, B_j, be defined by the order set:

$$B_j=\{X,V_j,W_j,f(X,V_j,W_j)\} \tag{6}$$

Using equation 6 the aggregate fuzzy set defines the K^{th} pattern class C_k is defined as

$$C_k=\bigcup_{j\in k} B_j \tag{7}$$

where K is the index set of those hyperboxes associated with class k. Note that the union operation in fuzzy sets is typically the max of all of the associated fuzzy set membership functions.

A. Memebership function

The membership function for the j^{th} hyperbox $b_j(A_h)$, $0\le b_j(A_h)\le 1$, must measure the degree to which the hth input pattern A_h falls outside of the hyperbox B_j formed by the min point V_j and the max point W_j. As A_h approaches 1, and when the point is contained within the hyperbox, $b_j(A_h,V_j,W_j)=1$. The resulting membership function is defined as

$$b_j(A_h)=\frac{1}{2n}\sum_{i=1}^{n}[\max(0,1-\max(0,\gamma\min(1,a_{hi}-w_{ji})))$$
$$+\max(0,1-\max(0,\gamma\min(1,v_{ji}-a_{hi})))] \tag{8}$$

where $A_h=(a_{h1},a_{h2},.....a_{hn})\in I^n$ is the hth input pattern,

$V_j = (v_{j1}, v_{j2}, ...v_{jn})$ is the min point and max point for b_j is $W_j = (w_{j1}, w_{j2}, ...w_{jn})$ and γ is the sensitive parameter $0 \le \gamma \le 1$, which governs how fast the membership value decreases outside the hyperbox as A_h and b_j increases.

IV. Fuzzy Min-Max Learning Algorithm

The supervised FMM learning algorithm consists of three steps:

Expansion: Identify the hyperbox that can expand and expand it. If an expandable hyperbox cannot be found, add a new hyperbox for that class.

Overlap Test: Determine if any overlap exists between hyperboxes from different classes.

Contraction: If overlap between hyperboxes that represent different classes does exist, remove the overlap by minimally adjusting each of the hyperboxes

A. Hyperbox Expansion

Given the *h*th training pair $(A_{h,} d_h)$, find the hyperbox B_j which provides the highest degree of membership, allows expansion if necessary and represents the same class as d_h the degree of membership is measured using equation 8. For the hyperbox B_j to expand to include A_h the following constraint must be met.

$$n\theta \ge \sum_{i=1}^{n} (\max(w_{ji}, a_{hi}) - \min(v_{ji}, a_{hi})) \quad (9)$$

If the expansion criterion has been met for hyperbox B_j min point of the hyperbox **is** adjusted using the equation

$$v_{ji}^{new} = \min(v_{ji}^{old}, a_{hi}) \quad (10)$$

and the max point is adjusted using the equation

$$w_{ji}^{new} = \max(w_{ji}^{old}, a_{hi}) \quad (11)$$

B. Hyperbox Overlap Test

Considering that the hyperbox B_j was expanded from the above step and that the hyperbox B_k represents another class and it is to be tested for possible overlap class. Assuming $\delta^{old} = 1$ initially, the four test cases is satisfied for each of the n dimension.

$case\ 1: v_{ji} < v_{ki} < w_{ji} < w_{ki},$

$case\ 2: v_{ki} < v_{ji} < w_{ki} < w_{ji},$

$case\ 3: v_{ji} < v_{ki} \le w_{ki} < w_{ji},$

$case\ 4: v_{ki} < v_{ji} \le w_{ji} < w_{ki}.$

C. Hyperbox Contraction

If $\Delta > 0$, then the Δth dimensions of the two hyperboxes are adjusted. To determine the proper adjustment to make, the same four cases are studied.

$Case\ 1: v_{ji\Delta} < v_{k\Delta} < w_{j\Delta} < w_{k\Delta},\ w_{j\Delta}^{new} = v_{k\Delta}^{new} = \dfrac{w_{j\Delta}^{old} + v_{k\Delta}^{old}}{2}$

$Case\ 2: v_{k\Delta} < v_{j\Delta} < w_{k\Delta} < w_{j\Delta},\ w_{k\Delta}^{new} = v_{j\Delta}^{new} = \dfrac{w_{k\Delta}^{old} + v_{j\Delta}^{old}}{2}$

$Case\ 3\text{i}: v_{j\Delta} < v_{k\Delta} < w_{k\Delta} < w_{j\Delta}, \text{and } (w_{k\Delta} - v_{j\Delta}) < (w_{j\Delta} - v_{k\Delta}),$ $v_{j\Delta}^{new} = w_{k\Delta}^{new}$

$Case\ 3\text{ii}: v_{j\Delta} < v_{k\Delta} < w_{k\Delta} < w_{j\Delta}, \text{and}(w_{k\Delta} - v_{j\Delta}) > (w_{j\Delta} - v_{k\Delta}),$ $w_{j\Delta}^{new} = v_{k\Delta}^{old}.$

$Case\ 4\text{i}: v_{k\Delta} < v_{j\Delta} < w_{j\Delta} < w_{k\Delta} \text{ and } (w_{k\Delta} - v_{j\Delta}) < (w_{j\Delta} - v_{k\Delta}),$ $w_{k\Delta}^{new} = v_{j\Delta}^{old}.$

$Case\ 4\text{ii}: v_{k\Delta} < v_{j\Delta} < w_{j\Delta} < w_{k\Delta} \text{ and } (w_{k\Delta} - v_{j\Delta}) > (w_{j\Delta} - v_{k\Delta}),$ $v_{k\Delta}^{new} = w_{j\Delta}^{old}.$

V. Iris Segmentation and Feature Extraction

Iris Segmentation plays very important role for detecting the iris patterns, Segmentation is to locate valid part of the iris for iris biometric [15], [18]. Finding the inner and outer boundaries (pupillary and limbic) are as shown in the Fig 1. Localizing it's upper and lower eyelids if they occlude, and detecting and excluding any overlaid occlusion of eyelashes and their reflection. The best known algorithm for iris segmentation is Daugman's intergro-differential operator to find boundaries of iris as defined.

$$\max_{(r,xo,yo)} \left| G_\sigma(r) * \frac{\partial}{\partial r} \oint_{r,xo,yo} \frac{I(x,y)}{2\pi r} ds \right| \quad (12)$$

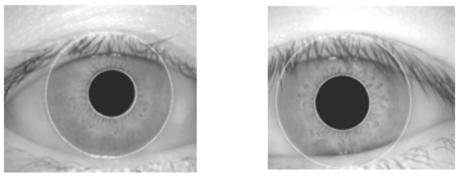

Fig. 4 Inner and Outer boundaries are detected.

Iris has a particularly interesting structure and provides rich texture information. Here we have implemented principal component analysis method for feature extraction which captures local underlying information from an isolated image. The result of this method yields high dimension feature vector. To improve training and recalling efficiency of the network, here we have reduced dimensionality of the feature vector by using Singular value decomposition (SVD) method. SVD is a method for identifying and ordering the dimensions along which the feature exhibit the most variation [19].This can be described as

$$X = UTV^T \quad (13)$$

the covariance matrix is be defined as:

$$C = \frac{1}{n} XX^T = \frac{1}{n} UT^2U^T \quad (14)$$

U is a $n \times m$ matrix. SVD performs repetitively order the singular values in descending order, if $n < m$, the first n columns in U corresponds to the sorted eigenvalues of C and if the first m corresponds to the sorted non-zero eigenvalues of C. The transformed data can thus be written as:

$$Y = \widetilde{U}^T X = \widetilde{U}^T UTV^T \tag{15}$$

where $\widetilde{U}^T U$ is a simple n x m matrix which is one on the diagonal and zero. Hence Equation 13 is decomposition of equation 13.

VI. EXPERIMENTAL RESULT

CASIA Iris Image Database includes 756 iris images from 108 eyes. For each eye, 7 images are captured in two sessions, where three samples are collected in the first session and four samples in second. For each iris class, we choose two samples from each session for training and remaining as testing samples. The timing analysis of training and recall, recognition rates in terms of number of hyperboxes, are as shown in Table.I and Table.II

TABLE I: TIMING ANALYSIS

	Training Time in Seconds	Recall time In seconds	Neurons in output layer/Hyperboxes
FNN	7.2367	145.5573	535
FMN	6.1303	125.1188	520

TABLE II: RECOGNITION RATES

Methodology	Recognition rate	Classifier
Daugman	99.25	HD,SVM
Wildes	97.43	Normalized Correlation
Y. Wang	99.57	WED
Ali	95.20	HD,WED
FMN	95.68	FMN

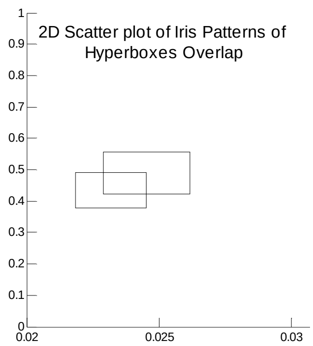

Fig. 5(a) Scatter plot Iris Patterns of Hyperboxes Overlap

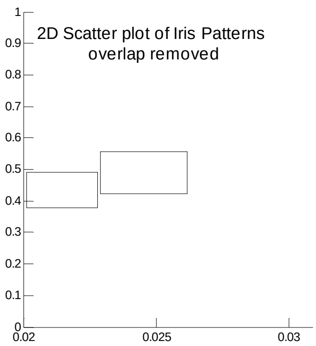

Fig. 5(b) 2D Scatter plot Iris Patterns Overlap removed

VII. CONCLUSION

A Supervised Neural Network Classifier that utilizes hyper box fuzzy set for Iris Recognition. The performance of FMN is analyzed and tested on CASIA database and also compared with other methodology. Hence the hyperboxes are created less in FMN. Therefore training and recall time is less than FNN. And also the recognition rates are compared in Table II.

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