Interval Type-2 Fuzzy Logic to the Treatment of Uncertainty in 2D Face Recognition Systems

Saad M. Darwish and Ali H. Mohammed

Abstract—**Uncertainty is an intrinsic part of intelligent systems used in face recognition applications. The use of new methods for handling inaccurate information about facial features is of fundamental importance. This paper deals with the design of intelligent 2D face recognition system using interval type-2 fuzzy logic for diminishing the effects of uncertainty formed by variations in light direction, face pose and facial expression. Built on top of the well-known fisher face method, our system employs type-2 fuzzy set to compute fuzzy within and in-between class scatter matrices of fisher's linear discriminant. This employment makes the system able to improve face recognition rates as the results of reducing the sensitivity to substantial variations between face images. Type-2 Fuzzy Sets (T2FSs) have been shown to manage uncertainty more effectively than Type-1 Fuzzy Sets (T1FS), because they provide us with more parameters that can handle environments where it is difficult to define an exact membership function for a fuzzy set. Experimental results for YALE and ORL face databases are given, which show the effectiveness of the suggested system for face recognition and also illustrate high accuracy when compared with other methods.**

Index Terms—**Face recognition, interval type-2 fuzzy logic, soft computing, image processing.**

I. Introduction

Machine recognition of faces is emerging as an active research area covering numerous disciplines such as image processing, pattern recognition, computer vision and biometrics. In the literatures, face recognition problem can be formulated as: given static (still) or video images of a scene, identify or verify one or more persons in the scene by comparing with faces stored in a database [1]. The quick development of face recognition is due to a combination of many subjects like: dynamic development of algorithms, the availability of large databases of facial images, and methods for evaluating the performance of face recognition algorithms. Face recognition is motivated by the need for wide spread applications in many areas such as surveillance, telecommunication, digital libraries, human computer intelligent interaction, smart environments, and security.

In practice, face recognition is a very difficult problem and mainly depends on several different factors such as [2] ,[3]: 1) Facial expression such as sadness, happiness, and facial pose. 2) Occlusion: faces may be partially occluded by other objects (like wearing glasses). 3) Imaging conditions like lighting and camera resolution. 4) Presence or absence of structural constituents like beards, mustaches and glasses. Face recognition is used for two major tasks: verification and identification. Face verification is a 1:1 match that compares a face image against a template face images, whose identity is being claimed. On the contrary, face identification is a 1: *N* problem that compares a query face image against all image templates in a face database to define the identity of the query face [2]. A good face recognition methodology should consider facial's features representation as well as classification issues.

Face recognition system generally consists of three stages [4]. The first stage includes detecting and localizing the face in arbitrary images. The second stage requires extraction of pertinent features from the localized image obtained in the first stage. Finally, the third stage involves classification of facial images based on derived feature vector. Face recognition depends heavily on the particular choice of features used by the classifier [5]. One usually starts with a given set of features and then attempts to derive an optimal subset of features leading to high recognition performance.

In order to design high accuracy face recognition system, the choice of feature extraction method is very vital. Two main approaches for feature extraction have been widely used in conventional techniques [2], [4]. The first one is based on extracting structural facial features such as shapes of the eyes, nose and mouth. These approaches deals with local information rather than global information, and therefore is not affected by inappropriate information in an image. However, because of the explicit model of facial features, the structure-based approaches are sensitive to irregularity of face appearance and environmental conditions. The second method is statistical-based approach that extracts features from the entire image and, therefore uses global information rather than local information. They also usually require large samples of training data.

In the current literature, face recognition approaches form a still image have basic three categories: holistic approach, feature based approach and hybrid approach [2], [4], [6]: 1) Holistic (global) approach: - uses the entire image as the pattern to be classified, thus using all information available in the image. The main advantage of these approaches is that they do not destroy any of the information in the images by focused on only limited regions or points of interest. However, they tend to be more sensitive to image variations. Holistic techniques can be subdivided into two groups: statistical (e.g. eigenvectors and Fisherfaces vectors) and AI

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approaches (e.g. Neural networks and machine learning techniques). 2) Feature-based approach: a set of local features is extracted from the image such as eyes; nose, mouth etc. that are used to classify the face. Standard statistical pattern recognition techniques are then employed to match faces using these measurements. The major benefit of this approach is its relative robustness to variations in illumination, contrast, and small amounts of out-of-plane rotation. The major disadvantage is the difficulty of automatic features detection. 3) Hybrid approach: in which both local features and the whole face is used as the input to the face detection system. It is more similar to the behavior or human being to recognize the face.

Soft computing techniques (e.g. fuzzy logic, genetic algorithms and swarm intelligence) have emerged as an essential methodology for dealing with uncertainty of numerous environmental conditions (including illumination, poses, etc.) that is always involved in face recognition applications and this is a common problem in pattern recognition [1], [7], [8]. Fuzzy logic is used for modeling human thinking and perception. In place of using crisp set (theory of binary propositions), fuzzy systems motive with fuzzy set of multi-values. However, it is not reasonable to use a precise membership function for something uncertain, so in this case what needed is another type of fuzzy sets, those which are able to handle these uncertainties, the so called type-2 fuzzy sets [9]. Type-2 fuzzy logic permits for better modeling of uncertainty as type-2 fuzzy sets encompass a Footprint of Uncertainty (FOU) that gives more degrees of freedom to type-2 fuzzy sets in comparison to type-1 fuzzy sets [10]. A type-2 membership function is actually a three dimensional membership function that characterizes a type-2 fuzzy set.

Unfortunately, type-2 fuzzy sets are more difficult to use and realize than traditional type-1 fuzzy sets. Therefore, their use is not widespread yet. Even in the face of these difficulties, type-2 fuzzy logic has found many applications. A short summary of existing applications on type-2 fuzzy sets can be found in [9], [11]. To reduce the complexity, interval type-2 fuzzy sets (IT2FS) have been used, since the secondary memberships are all equal to one [12]. So, only interval type-2 fuzzy logic systems are considered in the proposed face recognition system.

Reliable techniques for face recognition under more extreme variations caused by pose, expression, occlusion or illumination (highly nonlinear) have proven elusive. Based on the concept of fuzzy fisherface introduced by K. Kwak *et al.* [13], this paper proposes a modified version of the fisherface method for face recognition by including type-2 fuzzy information about class membership of the face. This type of fuzzy sets can efficiently manage the vagueness and ambiguity of the face images being degraded by poor environmental conditions. This is due to the ability of type-2 fuzzy systems to handle the high levels of uncertainty as a result of having additional degrees of freedom provided by the FOU.

The rest of the paper is organized as follows: Section II describes some of the recent related works. The detailed description of proposed system has been made in Section III. In Section IV, the results and discussions on the dataset are given. Finally conclusions are drawn in Section V.

II. Literature Survey

Automatic face recognition can be seen as a pattern recognition problem, which is very hard to solve due to its nonlinearity. Particularly, we can think of it as a template matching problem, where recognition has to be performed in a high-dimensional space [14]. Since higher the dimension of the space is, more the computation we need to find a match, a dimensional reduction technique is used to project the problem in a lower-dimensionality space. Really, the eigenfaces can be considered as one of the first approaches in this sense. Some authors [15], [16] adopted the PCA (Principal Component Analysis) for computing eigenfaces. As the PCA is performed only for training the system, this method results is to be very fast, when testing new face images.

LDA (Linear Discriminant Analysis) [17] has been proposed as a better alternative to the PCA that deals with the input data in their entirety, without paying any attention for the underlying structure. The main aim of the LDA consists in finding a base of vectors providing the best discrimination among the classes, trying to maximize the between-class differences, minimizing the within-class ones. In some approaches, such as the Fisherfaces [18], [19] the PCA is considered as a preliminary step in order to diminish the dimensionality of the input space, and then the LDA is applied to the resulting space, in order to perform the real classification. Recently, Independent component analysis (ICA) has been developed as an effective feature extraction technique that has been applied to image discrimination [2]. ICA captures discriminant features that not only exploiting the covariance matrix, but also considering the high-order statistics. In general, the main disadvantage of the PCA, LDA, ICA and Fisherfaces is their linearity.

A further nonlinear solution to the face recognition problem is given by the neural networks, largely used in many other pattern recognition problems, and readapted to cope with the people authentication task [8], [9]. The advantage of neural classifiers over linear ones is that they can reduce misclassifications among the neighborhood classes. Yet, because of the pattern dimensions, neural networks are not directly trained with the input images, but they are preceded by the application of such a dimensionality reduction technique. In the literature, some kind of neural networks have been tested in face recognition, in order to exploit their particular properties. For examples, Self-Organizing Map (SOM) is invariant with respect to minor changes in the image with respect to rotations, translations and scaling. Recent works in [7], [17] introduced a hybrid approach, in which through the PCA the most discriminating features are extracted and used as the input of a Radial Basis Function (RBF) neural network. The RBFs perform well for face recognition problems, as they have a compact topology and learning speed is fast.

Early work carried out on automatic face recognition was mostly based on feature-based techniques [4], [13], [20], [21]. More sophisticated feature extraction techniques are involved such as Hough transform and morphological operations.

However, all of these techniques rely heavily on heuristics such as restricting the search subspace with geometrical constraints. Another well-known feature-based approach is the elastic bunch graph matching method in which face recognition can be formulated as elastic graph matching that is performed by stochastic optimization of a matching cost function. However, this type of matching process is computationally expensive [4]. Regarding feature-based approach, in contrast to template matching, the models are learned from a set of training images, which should capture the representative variability of facial appearance. These learned models are then used for detection. In the template-based approaches, the correlations between an input image and the stored patterns are computed for detection. These techniques, match facial components to previously designed templates using appropriate energy function [4].

Lately, many approaches are introduced to cope with variation in face features spaces. These approaches classify into three kinds: invariant features, canonical forms, and variation- modeling [5], [6]. The first approach seeks to utilize features that are invariant to the changes being studied. For instance, the work presented in [22] is invariant to illumination and may be used to recognize faces when lighting conditions change. The second approach attempts to "normalize" away the variation, either by clever image transformations or by synthesizing a new image (from the given test image) in some "canonical" or "prototypical" form. In the third approach, the idea is to learn, in some appropriate subspace, the range of the variation in that space. This usually leads to some parameterization of the subspace(s). Recognition is then performed by choosing the subspace closest to the test image, after the latter has been appropriately mapped [14].

Many soft computing–based approaches are reported for facial features extraction ranging from the geometrical description of salient facial features to the expansion of digitized images of the face on appropriate basis of images [1]. Some researchers have also used fuzzy logic for face recognition. For example, the work in [23] divided the face into three regions (the eyes, the mouth, and the nose) and assigned each region to a module of the neural network. A fuzzy Sugeno integral was then used to combine the outputs of the three modules to make the final face recognition decision. Several of AI algorithms have been modified and/or enhanced to compensate for environments' variations and dimension as a result of which these approaches appear to produce better recognition results than the feature-based ones in general. Fuzzy LDA (Fuzzy Fisherface) recently, was proposed for feature extraction and face recognition [13], [18], [19]. Fuzzy LDA computes fuzzy within-class scatter matrix and between- class scatter matrix by incorporating class membership of the binary labeled faces (patterns) that showed a good discriminating ability compared to other methods like LDA and PCA under severe variation in lighting and facial expressions.

This paper presents a statistical face recognition system based on interval type-2 fuzzy LDA that is an extension of the type- 1 fuzzy LDA. In our proposed method, the membership values for each pattern vector are extended as interval type-2 fuzzy memberships by assigning uncertainty to the type-1 memberships. By doing so, the classification result obtained by type-2 fuzzy face recognition is found to be more reasonable than that of the crisp and type-1 fuzzy algorithms. In general, type-2 fuzzy logic systems have been shown to be very well suited to dealing with the large amounts of uncertainties present in the majority of real world applications [24].

III. Proposed Methodology

Fig. 1 shows the general data flow diagram of the proposed type-2 fuzzy–based face recognition system, which comes with better classification performance. The system utilizes PCA as data representation to project face patterns from a high-dimension image space to some low dimensional space while retaining as much variation as possible in the data set. Furthermore, it employs an enhanced approach for fuzzy fisherface classification that helps us to find the optimal classification –driven projections of face patterns that could establish a high degree of similarity between samples of the same class and a high degree of dissimilarity between samples of many classes. The following subsections discuss each step in details.

A. Feature Extraction Stage

This stage relies on transformation of face samples by utilizing PCA to derive a starting set of features. PCA is a well-known technique commonly exploited in multivariate linear data analysis. The main underlying concept is to reduce the dimensionality of a data set while retaining as much variation as possible in the data set [15]. Formally, Let a face image be a two-dimensional $n \times n$ array of pixels. The corresponding image z_i is viewed as a vector with n^2 coordinates that result from a concatenation of successive rows of the image. Symbolize the training set of N faces by $Z=\{z_1, z_2,..., z_N\}$. Express the corresponding covariance matrix R in the standard manner as [13]:

$$R = \frac{1}{N}\sum_{i=1}^{N}(z_i - \bar{z})(z_i - \bar{z})^T \tag{1}$$

$$\bar{z} = \frac{1}{N}\sum_{i=1}^{N} z_i \tag{2}$$

so, given a set of original face images Z their reduced feature vectors $X=(x_1, x_2,..., x_N)$ are obtained by projecting them into the PCA-transformed space as:

$$x_i = E^T (z_i - \bar{z}) \tag{3}$$

where $E = (e_1, e_2,..., e_r)$ be a matrix corresponding to the largest r eigenvalues, and x_i being the result of this transformation. The choice of the range of principal components r for dimensionality reduction takes into account both the spectral energy and the magnitude requirements. The eigenvalue spectrum of the covariance matrix provides a good indicator for meeting the energy criterion; one needs then to derive the eigenvalue spectrum of the within-class scatter matrix in the reduced PCA space to facilitate the choice of the range of principal components so that the magnitude requirement is met [18].

B. Interval Type-2 Fuzzy K–Nearest Neighbor

To improve the performance of the classifier, the proposed system utilizes interval type-2 fuzzy K-NN (IT2FKNN) to refinement of classification results so that they could affect the within-class and between-class scatter matrices [24]. This stage assigns membership as a function of the pattern distance from its K–nearest neighbor and those neighbor's memberships in the possible classes. In formal, given x_i as a set of feature vectors from the previous stage, IT2FKNN partition of these vectors specifies the degrees of membership of each vector to the classes. Let the partition matrix denoted by $u = [u_i]$ for i= 1,2, …, c (number of classes), the assigned membership of the face's pattern x is computed as [19]:

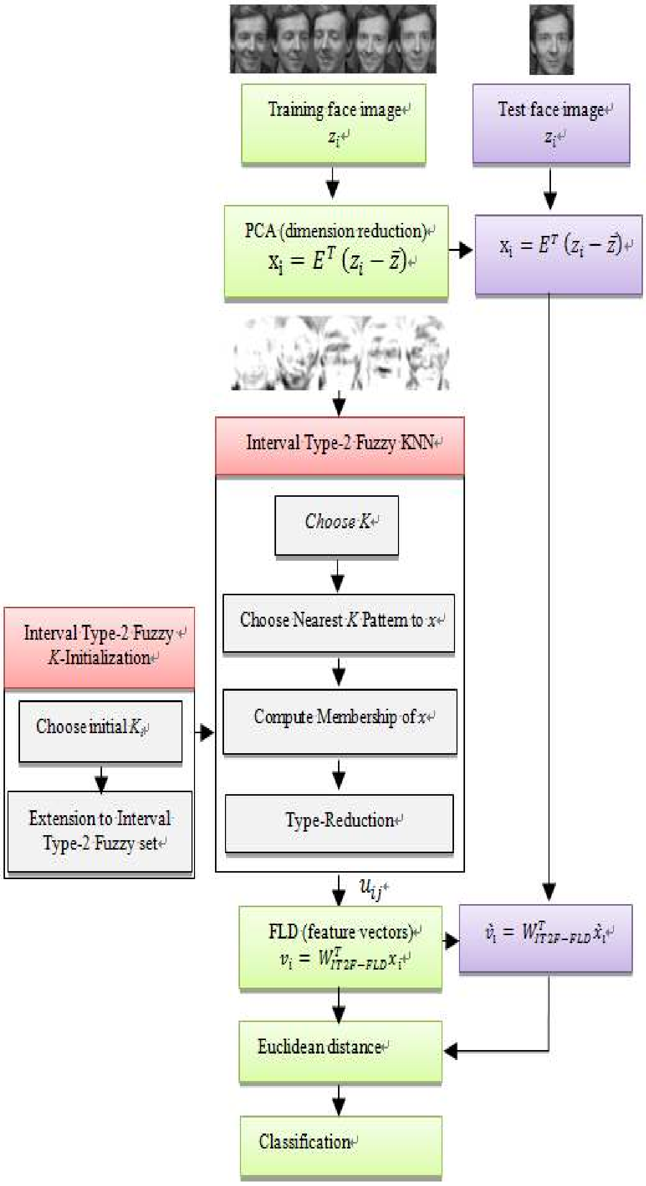

Fig. 1. Bock diagram of the proposed face recognition system.

$$u_i(x) = \frac{\sum_{j=1}^{k} u_{ij}(1/\|x - x_j\|^{2/(m-1)}}{\sum_{j=1}^{k}(1/\|x - x_j\|^{2/(m-1)})} \tag{4}$$

where u_i represents the interval type-2 fuzzy membership of x for class i , u_{ij} denotes initial interval type-2 membership of x_j, which is the j^{th} nearest neighbor to x in class i, and m symbolizes degree of fuzzification. In this case, several initial K values for KNN algorithm are used to manage and control the uncertainty for selecting an appropriate initial k for the initialization process.

This phase consists of 2 stages. In the first stage, we perform Interval Type-2 Fuzzy K-Initialization to extend pattern set to interval type-2 fuzzy sets. This is used for determining the elements of primary memberships on IT2FS. In the next stage, we perform interval type-2 fuzzy K-NN with interval type-2 fuzzy set. In this part, we assign interval type-2 fuzzy membership for a given pattern using the union operation. Finally, when we classify pattern by membership grade, we perform type- reduction and defuzzification. In this process, we can reduce redundant primary membership values. However, since we use an IT2FS, we not consider secondary grade, that is always 1.0. Herein, a specific relation between initial K and primary membership is as:

$$1 \le U_{r=1}^{n} u(j, k_r, x_i) \le n, k_r = \{k_1, k_2, ..., k_n\} \tag{5}$$

where, $u(j, k_r, x_i)$ characterizes the primary membership of the i^{th} face pattern in class j when initial K is selected as k_r. Furthermore, the primary memberships of each face can be represented as:

$$u_i(x_N) = u_{1_{iN}} + ... + u_{R_{iN}} = \sum_{r=1}^{R_{iN}} u_{r_{iN}} \tag{6}$$

R_{iN} denotes the number of primary membership for x_N with the number of primary memberships for K nearest neighbor patterns. To extend the primary membership for given pattern to an IT2FS, Eq. (6) turns into:

$$u_i(x_N) = \sum_{r=1}^{R_{iN}} 1.0 \big/ u_{r_{iN}} \tag{7}$$

for the type reduction process, the type-reduced membership of x_N in class i can be expressed as:

$$\bar{u}_i(x_N) = \frac{\sum_{r=1}^{R_{iN}} f(u_{r_{iN}}) u_{r_{iN}}}{\sum_{r=1}^{R_{iN}} f(u_{r_{iN}})} = \frac{\sum_{r=1}^{R_{iN}} 1.0 \times u_{r_{iN}}}{\sum_{r=1}^{R_{iN}} 1.0} = \frac{\sum_{r=1}^{R_{iN}} u_{r_{iN}}}{n} \tag{8}$$

$f(u_{r_{iN}})$ is secondary grade. Therefore, it is approximately the average of primary memberships of interval type-2 fuzzy set.

In summary, in the type-l fuzzy case, only one initial K is selected to assign initial fuzzy memberships to the pattern data. If the selection of K is poor, an undesirable classification rate for the pattern data can be obtained. However, for the interval type-2 fuzzy approach, we need not select only one initial K. This is due to the extension of the pattern data into an interval type-2 fuzzy set. For this extension, we use initial K values in an appropriate range. Handling of this uncertainty can decrease the contribution of an undesirable initial K on the classification process for the patterns. Hence, this can provide a more reasonable classification result by managing the uncertainty for the selected initial K. Reader looking for more details can refer to [9], [10], [24].

C. FLD Classifier (Fisherface Linear Discriminant)

Taking into account the membership grades u_{ij} obtained from IT2FKNN, the statistical properties of the patterns such as the mean value and scatter covariance matrices are used find the optimal classification –driven projection of patterns. u_{ij} is incorporated into the definition of the between-class scatter matrix and within- class scatter matrix to get the fuzzy between-class scatter matrix and fuzzy within-class scatter matrix as follows [13]:

$$m_i = \frac{\sum_{j=1}^{N} u_{ij} x_j}{\sum_{j=1}^{M} u_{ij}} \quad (9)$$

$$S_b = \sum_{i=1}^{c} N_i \ (\widetilde{m_i} - \overline{m})(\widetilde{m_i} - \overline{m})^T \quad (10)$$

$$S_w = \sum_{i=1}^{c} \sum_{X_s \in C_i} \ (x_s - \widetilde{m_i})(x_s - \widetilde{m_i})^T = \sum_{i=1}^{c} S_{w_i} \quad (11)$$

where $\widetilde{m_i}$ is the mean vector of class i, $\overline{m}$ stands for the mean of all vectors (images), and both between-class fuzzy scatter matrix S_b and within-class fuzzy scatter matrix S_w incorporate the membership values in their calculations. The optimal interval type 2 fuzzy projection $W_{IT2F-FLD}$ follows the expression [18]:

$$W_{IT2F-FLD} = \arg\max_W \frac{|W^T S_b W|}{|W^T S_W W|} \quad (12)$$

In this case, the feature vector transformed by interval type-2 fuzzy fisherface method follows the expression:

$$v_i = W_{IT2F-FLD}^T x_i = W_{IT2F-FLD}^T E^T (z_i - \bar{z}) \quad (13)$$

IV. Experimental Results

In this section, an application to the face recognition is investigated to demonstrate the effectiveness of the employed system. In parallel, the proposed system is compared with state-of-the-art face recognition approaches like PCA (eigenfaces) [15], LDA (Fisherface) [17], Fuzzy Fisherface (FDA) [13], Fuzzy Inverse FDA [25], 2DFLD [19]. The algorithm is tested on YALE and ORL database to compute recognition rate. The ORL (http://www.cam-orl.co.uk) database contains 40 persons, each having 10 different images. The images of the same person are taken at different times, under lightly varying lighting conditions and with various facial expressions. Some people are captured with or without glasses. The heads in images are slightly titled or rotated. The images in the database are manually cropped and rescaled to 56×46. Fig. 2 shows 10 images of one person in ORL. The YALE face database (http://cvc.yale.edu/) contains 165 face images of 15 individuals. There are 11 images per subject, one for each facial expression or configuration: center-light, glasses/no glasses, happy, normal, left-light, right-light, sad, sleepy, surprised and wink. Each image was digitized and presented by a 61×80 pixel array whose gray levels ranged between 0 and 255. Some of face images of the Yale databases are shown in Fig. 3.

Fig. 2. Sample faces of the ORL database.

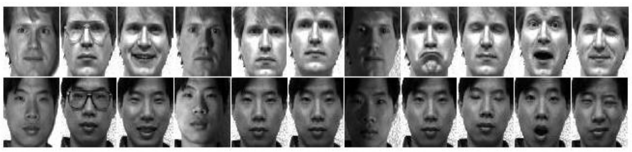

Fig. 3. Sample faces of the YALE database.

The experiments are implemented on Xeon 2.66 GHz machine with 4GB RAM equipped with operating system Windows XP professional platform and programmed in the MATLAB language (version 7.01). In our experiments, we split the whole database into two parts evenly. One part is used for training and the other part is for testing. In order to make full use of the available data and to evaluate the generalization power of algorithm more accurately, we adopt across-validation strategy and run the system 10 times. In each time, f face images from each person are randomly selected as training samples, and the rest is for testing. The FKNN parameter K is set as K=f-1 for Fuzzy Fisherface (FDA) algorithm in [13]. The justification for this choice is that each sample should have f-1 samples of the same class provided that within-class samples are well clustered [19].Furthermore, in all the experiments, m that represents the degree of fuzzification is taken equal (2) [25].

The first experiment was performed using different images per class for training, and the remaining images for testing. For feature extraction, we used respectively PCA, LDA, fuzzy Fisherface, fuzzy inverse FDA, 2DFLD and the proposed system. Note that all methods involve a PCA phase. The average recognition rates across 10 runs of each method is given in Table I for both ORL and Yale face databases. As we can see, the proposed interval type-2 fuzzy fisherface outperformed other classification techniques. Since other Fuzzy-based recognition methods may preserve unwanted variations due to lighting and facial expression, the recognition show a poor performance. In contrast, we note that the proposed system can be valuable in huge environmental conditions variation. In our opinion, the overlapping sample's distribution information is incorporated in the definitions of corresponding scatter matrices by type-2 fuzzy set theory, which is important for classification make the suggested system outperforms other methods.

TABLE I: Average Recognition Rate on the Face Databases

Methods/Features	ORL database	YALE database
PCA	0.8918	0.8533
LDA	0.9004	0.9333
FDA	0.8232	0.8533
Fuzzy Inverse FDA	0.8867	0.8857
2DFLD	0.9417	0.9600
Proposed System	**0.9604**	**0.9800**

TABLE II: Computing Time of the Feature Extraction Methods

Feature Extraction Methods	Time in Sec.
Eigenfaces (PCA)	0.0714
LDA	0.0840
FDA	0.0915
Proposed IT2FDA	0.1281

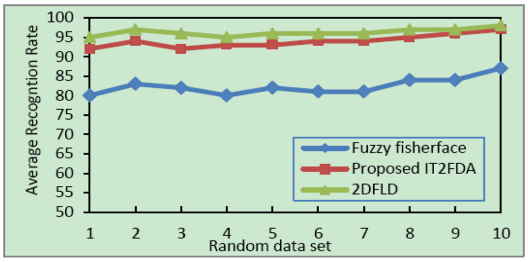

Fig. 4. Recognition Rate for ORL database.

In the second experiment, the recognition rate as performance index of different face recognition algorithms are plotted with number of images per subject used for training. From Fig. 4 we can see that the proposed system outperforms the other methods for every number of training samples for each class. This is because, the proposed system can extract more discriminative feature, in which using IT2FKNN to get the membership degree matrix, FDA with the redefined fuzzy within-class scatter matrix and fuzzy between-class scatter matrixes more efficiently captures the distribution of samples than LDA and FDA. In other words, we may suggest that the classification results of our method that depends on interval type -2 fuzzy K-NN is more reliable than the FDA method that depends on fuzzy K-NN regardless of what value of initial k we select.

The measure of the computing time is a very simple task. We only have to take the time right before and after the feature extraction process. Table II shows the computation time to obtain each feature using the above notebook configuration. As shown the highest time corresponds to the proposed method. For real-time face recognition, the proposed system is with an acceptable speed since it needs feature extraction technique with database building and searching computations. Second, with respect to the computational complexity of the system, assuming that the size of the face image under consideration is $n \times n$, N is the total number of images, and N_k is the total number of initial K required for KNN algorithm, the complexity is $O(n^2 \times N \times N_k)$. Overall, the complexity of the proposed system is roughly $O(n^2)$, which gives us a chance to discover the opportunity of integrating the system with other tools for an integrated online face recognition mechanism entrenched inside an automated real-time examination system.

V. Conclusions and Discussions

This paper proposes a 2D face recognition system based on fisher discriminant criterion and fuzzy set theory. The system calculates membership degree matrix through a generalized version of fuzzy KNN algorithm called interval type-2 fuzzy KNN that includes refined information about class membership of the patterns. By doing this, the system is able to reduce sensitivity variations between face images caused by varying illumination, viewing conditions and facial expressions.

Unlike previous face recognition efforts based on fuzzy fisherface in which the number of neighbors in KNN classifier is usually experiment-driven and needs to be adjusted for a specific dataset at hand, our system is based on interval type-2 fuzzy set to extend the membership values of each pattern as interval type 2 fuzzy memberships by using several initial K in order to handle and mange uncertainty that exist in choosing initial K. Experiments on the Yale and ORL face databases show that the proposed system can work well and exhibits a steadily better classification rate in comparison to other standard methods. As a further study, we plan to examine generalized type-2 fuzzy sets such as zSlices to improve system classification.

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