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Fuzzy based Pixel wise Information Extraction for Face Recognition

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***Abstract*—This paper brings out a new approach of information extraction based on fuzzy logic, which can be used for robust face recognition system. We have applied a fuzzification operation to extract the pixel wise association of face images to different classes. The fuzzification operation uses π membership function to obtain the degree of belonging of a particular pixel to all classes. Further nearest neighbor classification using correlation coefficient and principal component analysis are used to obtain the classification error over AT&T face database. The results clearly confirmed the superiority of proposed approach.**

***Index Terms*—Face recognition, fuzzy logic, information extraction, π membership.**

I. Introduction

Within the last several years, face recognition has been very active research area of computer vision. This is because of its wide range of applications, from identity authentication, access control, law enforcement and surveillance to human-computer interaction [1], [2]. Consequently, many algorithms have been proposed [4]-[7], [10]-[15]. Even though current machine recognition systems have reached a certain level of maturity, their success is limited by the real applications constraints, like pose, illumination and expression. A face as a three-dimensional object subject to varying constraints and it is to be identified based on its two-dimensional image, inherently limits the recognition rate [3].

Broadly, face recognition methods can be categorized into two groups: feature-based and appearance-based. In feature-based approach, a set of local features is extracted from the image such as eyes, nose, mouth etc. and they are used to classify the face. The major benefit of this approach is its relative robustness to variations in illumination, contrast, and small amounts of out-of-plane rotation. But there is generally no reliable and optimal method to extract an optimal set of features. Another problem of this approach is that it may cause some loss of useful information in the feature extraction step. The appearance-based approaches use the entire image as the pattern to be classified, thus using all information available in the image. However, they tend to be more sensitive to image variations. Thus major issue of designing an appearance-based approach is the extraction of useful information which can be used for efficient face recognition system that is robust under different constraints (pose, illumination, expressions etc.) [4], [6]. In this paper we are utilizing appearance-based approach of face recognition in our implementation.

When using appearance-based approach, an image of size *m*x*n* pixels is represented as a vector in *mn*-dimensional space. But for an efficient and fast recognition system, the *mn*-dimensional space is quite large. This generates the need for dimension reduction algorithms. While reducing the dimension, these algorithms must also possess enhanced discrimination power. Some of the most used algorithms are principal component analysis (PCA), linear discriminant analysis (LDA), and independent component analysis (ICA) [5]-[7]. These linear algorithms project data linearly from high dimensional image space to a low dimensional subspace. Since the entire image space along with constraints is highly non-linear, they are unable to preserve the non-linear variations necessary to differentiate among different classes. Due to this, the linear methods fail to achieve high face recognition accuracy [3].

Soft computing techniques (artificial neural networks, fuzzy logic and genetic algorithms) have emerged as an important methodology for analysis in computer vision research. Artificial neural network is a powerful tool to resolve the nonlinearity imposed by different constraints [12], [13]. Similarly, fuzzy logic [16], [17] is used for modeling human thinking and perception [18]. In place of using crisp set (theory of binary propositions), fuzzy systems reason with fuzzy set of multi-values. It is well established that the effectiveness of human brain is not only from precise cognition, but also from analysis based on fuzzy set and fuzzy logic. Uncertainty is always involved in real application constraints and this is a common problem in pattern recognition. Analysis based on fuzzy logic has proved to generate substantial improvement in pattern recognition results [8], [9], [14], [15], [18].

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Ghosh et al. used fuzzy logic to obtain the feature-wise degree of belonging of a pattern to all classes for remote sensing and some other application [8], [9]. The existing face recognition algorithms, which utilize the power of fuzzy logic, are exploiting the fuzzy k-nearest neighbor classification [24] in order to incorporate the benefit of fuzzy logic in their approach [14], [15]. Kwak et al. gave a generalized version of Fisher-face approach for face recognition by incorporating the refined information of class membership of the binary labeled faces. They used first PCA for feature extraction and dimension reduction, then on features transformed by PCA, fuzzy k-nearest neighbor classification is used to find the within and between class scatter matrices [14]. Similar concept is used by Yang et al. with integration of discriminative information present in the null space of the fuzzy within class scatter matrix [15].

The effect of class wise belonging of individual pixels in face recognition is not yet discovered. The present investigation explores association of different pixel values of facial images to different classes.

The rest of the paper is organized as follows. The detailed description of proposed approach has been made in Section 2. Along with this, the brief overview of prerequisite algorithms is also given. In Section 3, the results and discussions on the data set are given. Finally conclusions are drawn in Section 4.

II. Proposed Approach of Face Recognition

The present article proposes a new approach of *fuzzy* based *pixel* wise *information extraction* (FPIE) for face recognition. FPIE evokes pixel wise information of face images to different classes and thus collects pixel wise belonging to different classes to reduce classification error. The block diagram of implementation of our face recognition system is illustrated in Fig.1. The database images are read in column vector form and on these, we apply fuzzification process (FPIE). One fuzzy vector is generated corresponding to one face image. Nearest neighbor classification is applied on these fuzzy vectors. Each module of our approach of face recognition is further explained as follows.

A. Fuzzy based Pixel wise Information Extraction (FPIE)

FPIE module generates pixel wise degree of association of a face image to different classes using membership function (MF). This takes a face image as an input and using MF, fuzzifies the pixel values of the image. This generates the membership of individual pixel to different classes.

The concept of MF is basically the generalization of characteristic function of a crisp set. The characteristic function of a crisp set assigns a value of 1 to the member and 0 to non member to discriminate between member and non member elements in the universal set [16].

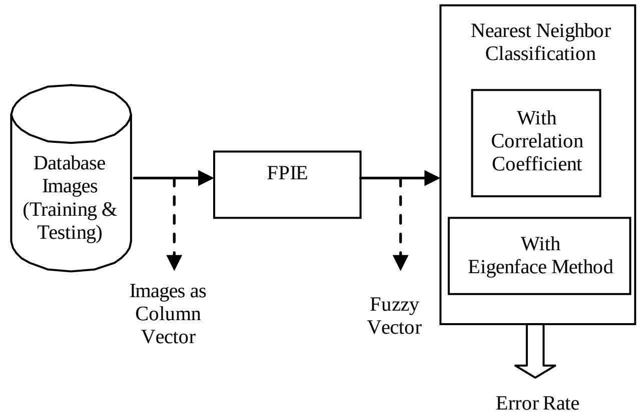

Fig.1. Block diagram of system architecture.

This function can be generalized such that the values assigned to the elements of the universal set fall within a specified range which may be the unit interval [0, 1]. Thus these values, which are real numbers in [0, 1], express the membership grade of the elements of the universal set. Larger values indicate higher degrees of set membership. We can express the MF as mapping function μ_A for fuzzy set A as follows:

$$\mu_A : \mathbf{z} \rightarrow [0, 1] \tag{1}$$

where $\mathbf{z}$ is the universal set under consideration.

In the appearance-based face recognition system, the universal set is generated by pixel values of 2-dimensional face image. A face image can be represented as a $m \times n$ dimensional matrix with m number of rows and n number of columns. This can be expressed in the form of mn dimensional vector $\mathbf{z}$ as:

$$\mathbf{z} = [z_1, z_2, \ldots, z_d, \ldots, z_D]^T. \tag{2}$$

Here D denotes total number of data points in a pattern, which are total number of pixels (mn) in the face image. FPIE module takes each image of the database in vector form to fuzzify by MF.

We have used a π-type MF for fuzzification [8], [16], [17]. This comprises a parameter, named fuzzifier (m), which can be tuned as per the requirement of the problem and thus provides more flexibility and generalization capability for classification. As shown in Fig. 2, the shape of this type of function is similar to that of Gaussian function. By varying the value of fuzzifier m, the steepness of MF can be controlled. The function is given by

$$\begin{aligned}
\pi(z;\alpha,\gamma,\beta) &= 0, & z &<= \alpha \\
&= 2^{m-1}\,[\,(z-\alpha)/(\gamma-\alpha)]^m, & \alpha &< z <= c1 \\
&= 1 - \; 2^{m-1}\,[\,(\gamma-z)/(\gamma-\alpha)]^m, & c1 &< z <= \gamma \\
&= 2^{m-1}\,[\,(z-\gamma)/(\beta-\gamma)]^m, & \gamma &< z <= c2 \\
&= 1 - \; 2^{m-1}\,[\,(\beta-z)/(\beta-\gamma)]^m, & c2 &< z < \beta \\
&= 0, & z &>= \beta
\end{aligned} \tag{3}$$

where $c1$ and $c2$ are the two crossover points.

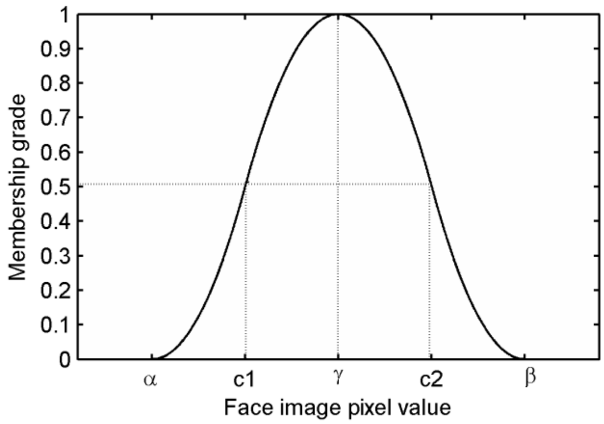

Fig.2. π-type membership function used for fuzzification of each face image.

α, β and γ represent the minimum, maximum and mean value of training data set for a particular data point (pixel). π-type MF provides 0.5 membership grade at $c1$ and $c2$ and maximum (1.0) at the center γ as shown in Fig.2. We have selected the value of m equal to 2 in the present investigation. The MF can be calculated based on minimum, center and maximum of a particular pixel number (p) in the training data using

$$\alpha = \min(p)$$
$$\beta = \max(p)$$
$$\gamma = \text{mean}(p) \qquad (4)$$

This function is symmetric about $z = \gamma$ and increases monotonically for data values between α and γ, while decreases for data values between γ and β. This provides the membership grade as 1 to the training data when its pixel value is at the center of the MF. The membership grade gradually decreases to reach 0.5 at cross over points $c1$ and $c2$ for training data, when it is away from the center. The region beyond $c1$ and $c2$ will provide membership grade less than 0.5. This is used to provide more generalization capability by our system to incorporate the variations uncovered by the training data. For a face image represented in vector form by Eq. 2, the membership grade vector after applying FPIE is expressed as:

$$\boldsymbol{g} = [g_1, g_2, \ldots, g_d, \ldots, g_D]^T. \qquad (5)$$

where g_d denotes the membership grade of the d^{th} pixel of face image $\boldsymbol{z}$.

B. Nearest Neighbor Classification

Classification (similarity search) is a very crucial step in any pattern recognition application. One of the most popular non-parametric techniques is the nearest neighbor classification (NNC), which simply states that the unclassified object is assigned to the class of its nearest neighbor (NN) among a set of design objects. NNC asymptotic or infinite sample size error is less than twice of the Bayes error [19]. Various variants of NNC are given in the literature [20]-[23]. The basic NNC rule behind these techniques is given by T. M. Cover et al. [19]. Some of the popular variants are k-nearest neighbor classifier (k-NNC) and nearest mean classifier (NMC). In k-NNC, instead of 1-NN, generally, k-nearest neighboring data objects are considered. Then, the class label of unseen objects is established by majority vote. The parameter k represents the number of neighbors involved. Tuning k as a way to regularize the NNC gives a trade-off between the distribution of the training data with a priori probability of the classes involved. When k = 1, the training data distribution and a priori probability are considered, while, when k = N, only a priori probability of the classes determines the class label. In NMC, we consider only the mean of each class, i.e. one prototype per class. In comparison to NNC, NMC has a high error on the training data and on the test data, but the error on the training data is a good prediction of the error on the test data. When considered as a regularized version of the NNC with one NN, i.e. 1-NNC, NMC has only one prototype per class instead of as many prototypes as the number of training objects. Thus it is evident that reducing the number of labeled prototypes is another way of regularizing the 1-NNC, where a high number of prototypes makes the classifier more (training data) specific and a low number makes it more general [23]. In the present investigation, we have used k-NNC with k as the number of images per subject in the training set for classification. Two variants of distance metrics are used to find NN of a test image in our classification engine. These are correlation coefficient and Euclidean distance in eigen space, explained in following subsections.

C. Correlation Coefficient

The correlation coefficient [4], [25]-[27] (corr. coeff.) between two images A(x, y) and B(x, y) is defined as

$$\text{Corr. Coef.} = \frac{\sum_s \sum_t [A(s,t) - \overline{A}\,][B(s,t) - \overline{B}\,]}{\left\{\sum_s \sum_t [A(s,t) - \overline{A}\,]^2 \sum_s \sum_t [B(s,t) - \overline{B}\,]^2\right\}^{1/2}} \qquad (6)$$

where x = 0, 1, 2, …, M - 1, y = 0, 1, 2, …, N – 1, and the summation is taken over the whole image region, as we are taking the images A and B of same size. $\overline{A}$ and $\overline{B}$ are the average values of images A and B respectively. The value of correlation coefficient can vary from a negative value to highest possible value as one. Value one means accurate matching. So higher values of correlation coefficient imply better matching and maximum value of this among training images of different subjects is taken to probe the NN of a test image.

As correlation techniques are computationally expensive and require great amounts of storage, it is natural to pursue dimensionality reduction schemes. Sometimes face recognition in high-dimensional space may not give better recognition results, due to illumination variations, different face poses, diversified facial expression etc. Thus we need feature space of low-dimension as well as having high discrimination power between different classes. For this purpose we have used one simple algorithm, described in the next sub-section, to express the capability of proposed approach of information extraction for face recognition.

D. Principle Component Analysis

Principal component analysis (PCA) is one the most used technique under appearance based approach for dimension reduction [5]-[7]. We have implemented PCA procedure in our experiments as described by Turk et al. [5]. In a training set of M face images, let a face image is represented as a two dimensional N by N array of intensity values, or a vector of dimension N^2. Then PCA tends to find a M'-dimensional subspace whose basis vectors correspond to the maximum variance direction in the original image space. This new subspace is normally lower dimensional ($M' < M << N^2$). New basis vectors define a subspace of face images called face space. All images of known faces (training set) are projected onto the face space to find sets of weights that describe the contribution of each vector. If the image pixel values are considered as random variables, the PCA basis vectors are defined as eigenvectors of the scatter matrix S defined as:

$$S = \sum_{i=1}^{M} (x_i - \mu).(x_i - \mu)^T \qquad (7)$$

where μ is the mean of all images in the training set and x_i is the i^{th} face image in the training set represented as a vector i.e. its columns are concatenated in a vector form. A projection matrix W is generated using M' eigenvectors corresponding to M' largest eigenvalues of S, thus creating a M'-dimensional face space. As this face space is generated using eigenvectors of scatter matrix, sometimes this is also called as eigenspace.

The Euclidean distance is taken as the distance metric for the analysis in PCA. All images, the training as well as the test images are projected on W to generate the set of weights. Now the Euclidean distances are calculated between weights corresponding to the unknown face (test set) and known faces (training set). The minimum of these Euclidean distances is examined to find the NN of a test image. After checking the correctness of NN for all test images, the recognition results are generated.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, we will establish the utility of the proposed method of information extraction. For this purpose, the experiments are conducted on AT&T face database [28], [29]. This database comprises ten different images of each of forty distinct subjects. The images were taken with varying illumination, pose, expression and facial details (glasses / no glasses) and at different times. All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement). The images are stored as a 112×92 pixel array with 256 grey levels. Some sample images from this database are shown in Fig.3, which are face images of subject 10 and 19.

The error rate as performance index of different face recognition algorithms are plotted with number of images per subject used for training. The size of training set is varying based on number of images per subject used for training. If we take one image per subject for training, the training set size is 40, similarly for two images per subject; the training set size is 80 and so on. The remaining images of the database are used for testing. The images are taken sequentially from database to build training set and test set, i.e. if number of images per subject for training is four, then the first four images per subject are used in training set and remaining six images are used for testing. Table 1 lists the percentage error rate for different algorithm under varying size of training set. The corresponding graphs are drawn in Fig. 4, Fig. 5, Fig. 6 and Fig.7.

A. Error rate using k-NNC with corr. coeff.

The recognition results using *k*-NNC with corr. coeff. without FPIE are shown in Fig. 4. This shows the percentage error rate variation with number of images per subject used for training. This graph shows the performance variation when FPIE is not applied. It is evident from graph that the error rate decreases with increasing the size of training set. But it remains same 5% error rate for 7, 8 and 9 number of images per subject used for training. The system performance after applying FPIE using *k*-NNC with corr. coeff. is drawn in Fig. 5. As evident from the graph, significant reduction in error rate is obtained after applying FPIE and it reached zero percentage error rate for 9 images per subject used for training.

B. Error rate using k-NNC with PCA

Fig. 6 shows the percentage error rate variation using *k*-NNC with PCA when no fuzzification (FPIE) is applied. This also shows that the error rate decreases with increasing the size of training set. In this case, the percentage error rate ends with 2.5% for 9 images per subject used for training. Fig. 7 shows the system performance after applying FPIE using *k*-NNC with PCA. The significant reduction in error rate is obtained after applying FPIE and in this case also, it reached zero percentage error rate for 9 images per subject used for training.

C. Performance improvement by using FPIE

The percentage reduction in error rate is listed in Table 2. This shows that the application of FPIE significantly reduces the percentage error rate in both cases i.e. with corr. coeff. and PCA.

Reduction in percentage error rate is minimum as 14.29% to maximum as 100%. The mean value of this reduction is 38.43% with corr. coeff. and that is 37.12% with PCA.

Fig. 3. Sample images from AT&T face database

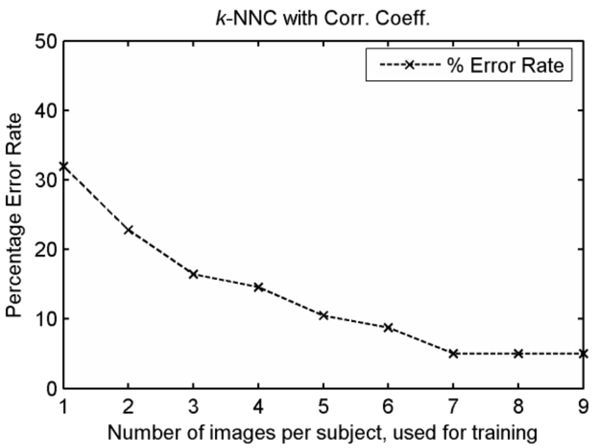

Fig. 4. Error rate variation of *k*-NNC with corr. coeff.

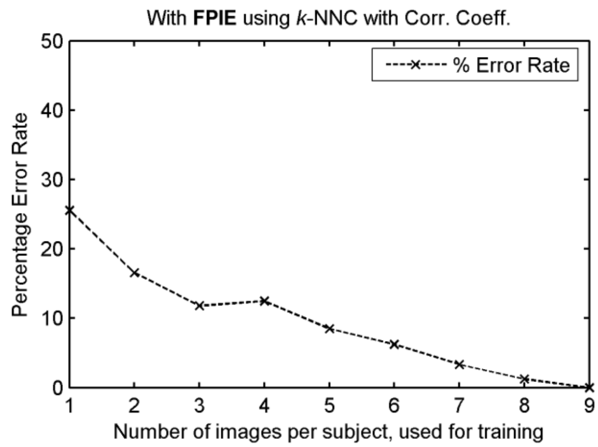

Fig. 5. Error rate variation with FPIE of k-NNC with corr. coeff.

TABLE I. COMPARISON OF PERCENTAGE ERROR RATE

Methodology	Number of images per subject used for training								
	1	2	3	4	5	6	7	8	9
k-NNC with Corr. Coef.	31.94	22.81	16.43	14.58	10.50	8.75	5.00	5.00	5.00
k-NNC with PCA	31.94	22.81	16.43	15.42	12.50	10.63	5.83	5.00	2.50
With FPIE using *k*-NNC with Corr. Coef.	25.56	16.56	11.79	12.50	8.50	6.25	3.33	1.25	0
With FPIE using *k*-NNC with PCA	26.11	16.56	13.57	11.67	9.00	7.50	5.00	1.25	0

TABLE II. PERCENTAGE REDUCTION IN ERROR RATE

Methodology	Number of images per subject used for training								
	1	2	3	4	5	6	7	8	9
Percentage reduction in error rate by using FPIE with Corr. Coef.	20.00	27.40	28.26	14.29	19.05	28.57	33.33	75.00	100
Percentage reduction in error rate by using FPIE with PCA	18.25	27.40	17.39	24.32	28.00	29.41	14.29	75.00	100

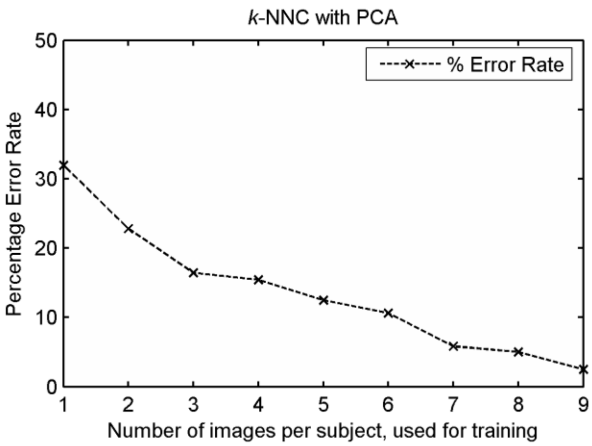

Fig. 6. Error rate variation of *k*-NNC with PCA.

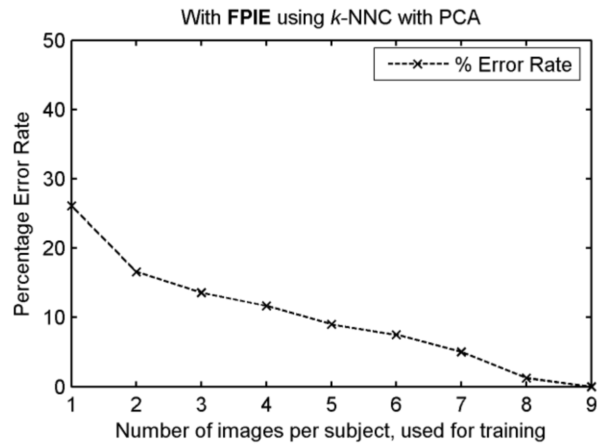

Fig. 7. Error rate variation with FPIE of *k*-NNC with PCA.

IV. Conclusion

A novel approach of fuzzy based information extraction for face recognition is presented in this paper. This approach unifies the capability of fuzzy set theory to obtain the degree of belonging of different pixels of a face image to different classes. We obtained the membership grade vectors for each face image of training and test set. To find the NN of a test vector, we have used two variants of distance metric. One is maximum value of correlation coefficient and the other is minimum value of Euclidean distance in eigenspace. We obtained the average reduction in error rate as 38.43% with correlation coefficient and 37.12% with PCA. This shows the significant improvement in classification accuracy by application of FPIE.

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