Fuzzy Moments Method for Face Recognition in an Ethnic Database

Rohollah Akbari[1] and Saeed Mozaffari[2]

[1]Electrical and Computer Department, Islamic Azad University of Qazvin, Qazvin, Iran
[2]Electrical Department, Semnan University, Semnan, Iran
r_akbari@yahoo.com, mozaffari@semnan.ac.ir

Abstract

So far, numerous methods have been proposed for face recognition based on single image person. In this paper, we introduce a new recognition algorithm based on feature vectors of three types of moments and fuzzy combination of them. We used an ethnic database in our experiments that are distinctly different from other famous databases such as AR and FERET. In ethnic database women have Hijab that is important feature in Muslim community such as Arabian countries. Also most of men have beard or mustache in these nations. Experimental results show that these features increase the recognition rate. Really, these characteristics eliminate the false recognition between male and female in the process. Subsets of 100 images from ethnic, AR and FERET are used in our experiments. Proposed method achieves 96% accuracy for ethnic database that is higher than two other databases.

Keywords-*face identification; ethnic database; one image per subject; moments feature vectors; distance measures; order comparator*

1. Introduction

Face is one of the most important human's biometrics which is used frequently in every day human communication. Face images convey significant amount of information including identity, emotional, age, and gender and etc. Extraction these information from facial images is still an active research field.

Face recognition based on image is a challenging task in pattern recognition which has many applications in the fields like person identification and verification, video surveillance, and human-computer interaction.

One of the main challenges faced by the current face recognition techniques lies in the difficulties of collecting samples. Fewer samples per person mean less laborious effort for collecting them, lower cost for storing and processing them. Unfortunately, many reported face recognition techniques rely heavily on the size and representative of training set, and most of them will suffer serious performance drop or even fail to work if only one training sample per person is available to the systems. This situation is called "one sample per person" problem: given a stored database of faces, the goal is to identify a person from the database later in time in any different and unpredictable poses, lighting, etc. from just one image. Such a task is very challenging for most current algorithms due to the extremely limited representative of training sample. Numerous techniques have been developed to attack this problem and all of them are categorized in three methods: holistic, local and hybrid. These methods are also listed in [1] and [2]. Beside them, the purpose of this paper is to introduce a new algorithm based on moment's methods to solve this problem and evaluation of its effects on ethnic face database.

At the side of above methods, most of the methods for face recognition are based on training processes using several samples for each person, such as: Support Vector Machines [3, 4], Neural Networks [5, 6]. Preparing multi training image samples from different point of views or different lightening conditions is usually difficult or even impossible in some applications like video surveillance or criminal cases.

In these non-training methods, first the input image is segmented into sub-images. Then, information for each image is extracted and feature vector is produced. Finally, with the help of a distance criterion, this vector is assigned to the closest class.

In this paper we proposed a new face recognition algorithm which is based on single image per person using three types of moments: Geometric, Legendre and Complex. Three fundamental issues related to their usefulness in image analysis are addressed. They include 1) sensitivity to image noise 2) aspects of information redundancy 3) capability for image representation [7]. In proposed algorithm, after partitioning the input image into seven segments, moments are obtained from each segment for a distinct order. Using these moments, the feature vector is constructed. This operation is also implemented on the other images in database and related feature vectors are extracted. Afterward, the input vector and the database vectors are compared and the closes one is chosen as the recognized person. To improve accuracy, the order comparator technique is implemented. Finally a fuzzy combination of three types of moments is used for last precision enhancement. To evaluate the proposed algorithm, we used a subset of ethnic; AR [8] and FERET [9] image databases each including 100 images. The AR and FERET databases are available from [10] and [11]. Some samples are shown in Figure 1 and Figure 2.

Figure 1. Some Samples from Ethnic Database

Figure 2. Some Samples from AR (first row) and FERET (second row) Databases

2. The Proposed Face Recognition Algorithm

The proposed algorithm is based on single image per person, Fig.3. In this method, first input and database images are segmented into 4 partitions. Then moment feature vectors of a definite order for all images are extracted. After this step, distance measure is used for finding minimum distance between input vector and other vectors and the related person is recognized. Then order comparator is performed to increase the accuracy. For an input test image, the proposed method is implemented for three types of moments (Geometric, Legendre and Complex) separately and finally a fuzzy combination of these three states is used for final decision.

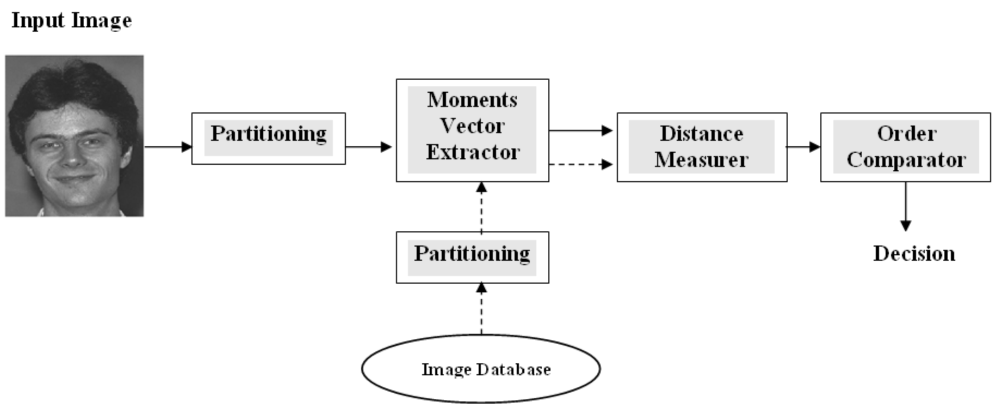

Figure 3. The Proposed Face Recognition Algorithm using Moment Feature Vectors

2.1 Image Partitioning

Since the proposed algorithm utilizes only one image per person, the input image is required to be partitioned into sub-images to increase the face recognition accuracy. At the end, the algorithm use these partition's information to recognize the input image. In this paper, all images including the input image and samples in the database are partitioned in the same manner. According to Fig.4, each image is segmented into 6 partitions, each including *at least* one face feature (eye, eyebrow, nose, mouth). Regarding the original frontal image, now we have 7 partitions.

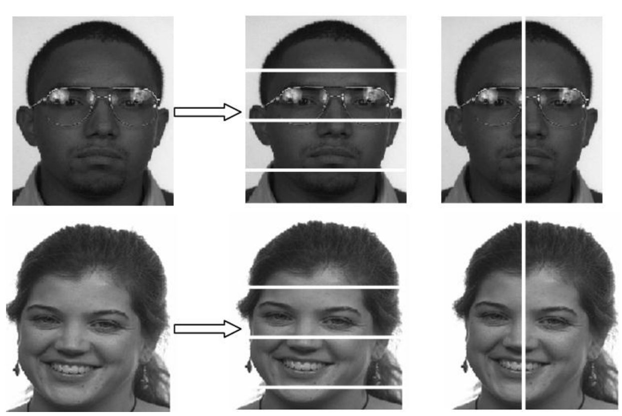

Figure 4. Image Partitioning

2.2 Methods of Moments

In this section we introduce three types of moments that are same in order formula (*complex, geometric and Legendre moments*) [7]. They have special characteristics that make them appropriate to use in our proposed algorithm such as: information redundancy, noise sensitivity and capability for image representation. In the following each of them are defined.

2.2.1 Complex Moments (CM)

The notion of Complex Moments (CM) was introduced as a simple and straightforward way to drive moment invariants. The complex moments of order *(p+q)* are defined as:

$$C_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x+iy)^p (x-iy)^q f(x,y)dxdy \qquad (1)$$

Where p,q=0,1,2,….., ∞ and $i=\sqrt{-1}$.

The complex moment of order *(p+q)* is a linear combination with complex coefficients of the geometric moments {M_{rs}} satisfying $r + s = p + q$:

$$M_{rs} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^r y^s f(x,y)dxdy \qquad (2)$$

$$C_{pq} = \sum_{r=0}^{p} \sum_{s=0}^{q} \binom{p}{r}\binom{q}{s} i^{p+q-(r+s)}.(-1)^{q-s} M_{r+s,p+q-(r+s)}. \qquad (3)$$

In polar coordinates, the complex moment of order *(p+q)* can be written as:

$$C_{pq} = \int_{0}^{2\pi} \int_{0}^{\infty} r^{p+q} e^{i(p-q)\theta} f(r\cos\theta, r\sin\theta) r dr d\theta \qquad (4)$$

Thus, it is related to the rotational moments {D_{nl}} as:

$$D_{nl} = C_{1/2(n-l),1/2(n+l)} \qquad (5)$$

Where:

$$D_{nl} = \int_{0}^{2\pi} \int_{0}^{\infty} r^n e^{-il\theta} f(r\cos\theta, r\sin\theta) r dr d\theta \qquad (6)$$

From (4), the repetition of C_{pq} is defined as *(p – q)* and the complex moments {C_{pq}} are not independent.

2.2.2 Geometric Moments (GM)

The Geometric Moment (GM) of order (*p+q*) of image *f(x,y)* are defined as:

$$M_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^p y^q f(x,y)dxdy \qquad (7)$$

Where p,q=0,1,2,….., ∞. The above definition has the form of the projection of the function *f(x,y)* onto the monomial $x^p y^q$. However, the basis set {$x^p y^q$}, while complete (Weierstrass approximation theorem [12]), is not orthogonal.

2.2.3 Legendre Moments (LM)

The Legendre Moments (LM) of order *(p+q)* is defined as:

$$\lambda_{pq} = \frac{(2p+1)(2q+1)}{4} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} P_p(x) P_q(y) f(x,y) dxdy \quad (8)$$

Where p,q=0,1,2,….., ∞. The Legendre polynomials { $P_p(x)$ } are complete orthogonal bases set on the interval [-1 1]:

$$\int_{-1}^{1} P_p(x) P_q(x) dx = \frac{2}{2p+1} \delta_{pq} \quad (9)$$

The qth-order Legendre polynomial is:

$$P_q(x) = \sum_{j=0}^{q} a_{qj} x^j = \frac{1}{2^q q!} \frac{d^q}{dx^q} (x^2 - 1)^q \quad (10)$$

By the orthogonality principle, the image function *f(x,y)* can be written as an infinite series expansion in terms of the Legendre polynomials over the square [-1≤x,y≤1]:

$$f(x,y) = \sum_{p=0}^{\infty} \sum_{q=0}^{\infty} \lambda_{pq} P_p(x) P_q(y) \quad (11)$$

Where the Legendre moments { λ_{pq} } are computed over the same square. If only Legendre moments of order ≤N are given, then the function *f(x,y)* can be approximated by a continuous function which is a truncated series:

$$f(x,y) \approx \sum_{p=0}^{N} \sum_{q=0}^{p} \lambda_{p-q,q} P_{p-q}(x) P_q(y) \quad (12)$$

2.3 Distance Measures

Some different distance criteria have been utilized in this paper to measure the distance between moment vector of input image and corresponding vectors in the database images.

If we have two moment's vectors of same length then we can calculate the following distances between these vectors [13].

- Euclidean Distance:

$$d(X,Y) = \|X - Y\| = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (13)$$

- Correlation Distance:

$$d(X,Y) = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{(n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2)(n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2)}} \quad (14)$$

- Cosine Distance:

$$d(X,Y) = -\cos(X,Y) = -\frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2}} \qquad (15)$$

- Manhattan Distance (city block distance):

$$d(X,Y) = \sum_{i=1}^{n} |x_i - y_i| \qquad (16)$$

- Mean Square Error (MSE):

$$d(X,Y) = \frac{1}{n}\sum_{i=1}^{n} (x_i - y_i)^2 \qquad (17)$$

- Squared Euclidean distance (sum square error, SSE):

$$SSE = \|X - Y\|^2 = \sum_{i=1}^{n} (x_i - y_i)^2; \qquad (18)$$

- Minkowski distance (L_p Metrics):

$$d(X,Y) = L_p(X,Y) = \left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{\frac{1}{p}} \qquad (19)$$

- Chi square distance:

$$d(X,Y) = \sum_{i=1}^{n} \frac{(x_i - y_i)^2}{x_i + y_i}; \qquad (20)$$

- Canberra distance:

$$d(X,Y) = \sum_{i=1}^{n} \frac{|x_i - y_i|}{|x_i| + |y_i|}; \qquad (21)$$

- Modified Manhattan distance:

$$d(X,Y) = \frac{\sum_{i=1}^{n} |x_i - y_i|}{\sum_{i=1}^{n} |x_i| \sum_{i=1}^{n} |y_i|}; \qquad (22)$$

- Modified SSE-based distance:

$$d(X,Y) = \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2}; \qquad (23)$$

- Chebyshev distance:

$$d(X,Y) = \max_i (|x_i - y_i|); \qquad (24)$$

This equals the limit of the L_p Metrics:

$$\lim_{p\to\infty}\left(\sum_{i=1}^{n}|x_i - y_i|^p\right)^{\frac{1}{p}}; \qquad (25)$$

- Spearman's rank correlation:

$$d(X,Y)=\frac{n(\sum_{i=1}^{n}x_i y_i)-(\sum_{i=1}^{n}x_i)(\sum_{i=1}^{n}y_i)}{\sqrt{n(\sum_{i=1}^{n}x_i^{\,2})-(\sum_{i=1}^{n}x_i)^2}\sqrt{n(\sum_{i=1}^{n}y_i^{\,2})-(\sum_{i=1}^{n}y_i)^2}}; \qquad (26)$$

2.4 Order Comparator

There are various ranks for a distinct order ($p+q$) of complex, geometric and Legendre moments. For example, moments of order 3 can be calculated as four ranks: 1)$p=0,q=3$. 2)$p=1,q=2$. 3)$p=2,q=1$. 4)$p=3,q=0$.

In this paper, experimental results show that the order with $p=0$ (first rank) has the maximum accuracy respect to other values of p (other ranks) in face recognition, but these values can be used for precision augmentation of first rank. This work is done using Fig.5 algorithm. According to this method, if the input image is not recognized correctly using first rank, then it can be recognized using decision of other ranks. Indeed, the test image will be recognized correctly if the maximum number of other ranks can recognize it.

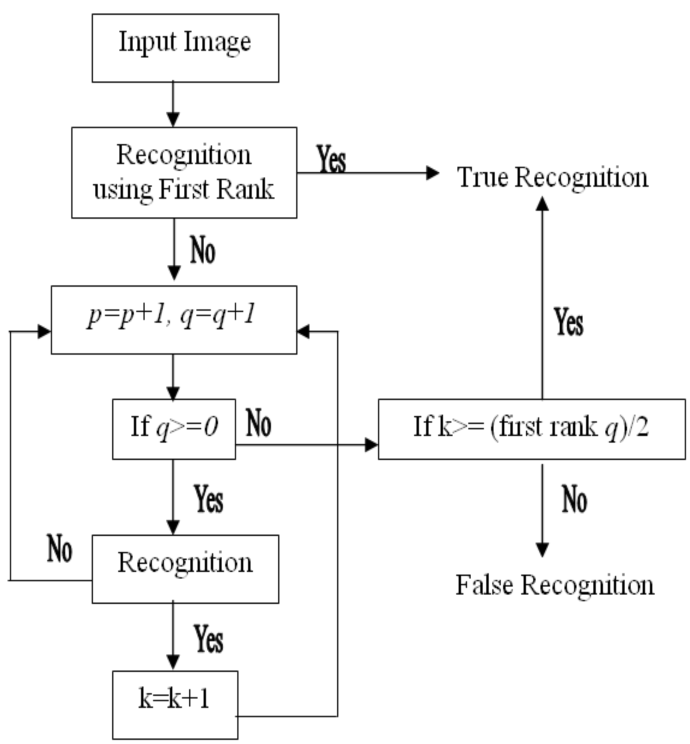

Figure 5. The Structure of Order Comparator

3. Fuzzy System

A fuzzy system is used for combination of results of three types of moments for performance enhancement of the recognizing system. Indeed, the input test image is recognized based on the results of Geometric, Legendre and Complex moments. The fuzzy system decides based on at least two identical results of three moments. Really, if the recognized person of two or three moments be same then that person will be accepted as the output of fuzzy system. The framework for the fuzzy system is shown in Fig.6. Membership function is Gaussian curve built-in type.

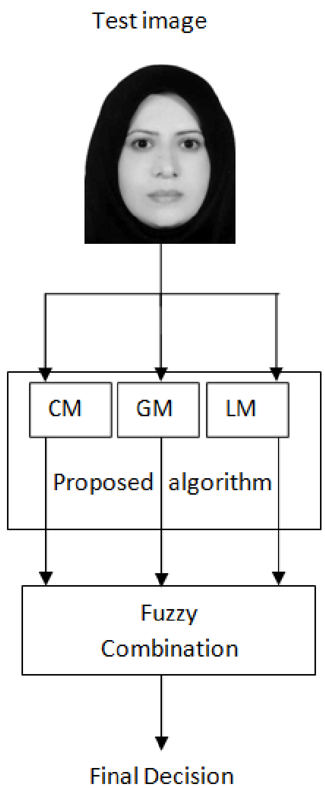

Figure 6. Fuzzy Fusion of Moments

4. Experimental Results

In this section experimental results of the proposed face recognition algorithm are reported on ethnic, AR and FERET databases.

As mentioned in the previous section, we used subsets of ethnic, AR and FERET image databases each including 100 images. All images were cropped and resized to 191×164 pixels. Each person in our experiments had two images. One image for neutral and another for smile or happiness expression. We put the neutral images as database and smilingly expression as test images.

In first experiment we evaluated the different distance measures effect on proposed algorithm accuracy using first rank of order1. Table I, shows the results.

Regarding to results in Table I, Modified SSE distance measure caused to maximum accuracy. Thus we used this distance measure in next experiments.

Table 1. Rates for Different Distance Measures

Distance Measures	*Database*		
	Ethnic	**AR**	**FERET**
Euclidean	90.0%	84.0%	85.0%
Correlation	87.0%	81.0%	85.0%
Cosine	88.0%	82.0%	84.0%
Manhattan	87.0%	81.0%	82.0%
MSE	90.0%	84.0%	87.0%
SSE	88.0%	82.0%	83.0%
Minkowski	86.0%	80.0%	83.0%
Chi square	83.0%	79.0%	81.0%
Canberra	78.0%	72.0%	73.0%
Modified Manhattan	93.0%	82.0%	85.0%
Modified SSE	96.0%	84.0%	86.0%
Chebyshev	79.0%	72.0%	74.0%
Spearman	81.0%	74.0%	75.0%

In second experiment the precision of proposed method was achieved for first rank (*p=0*) of different orders (Fig.7). The results showed that the precision was decreased with order enhancement. In addition, the results illustrates that the accuracy in the ethnic database is higher than two other databases. It is because of the features in men (beard and mustache) and women (Hijab).

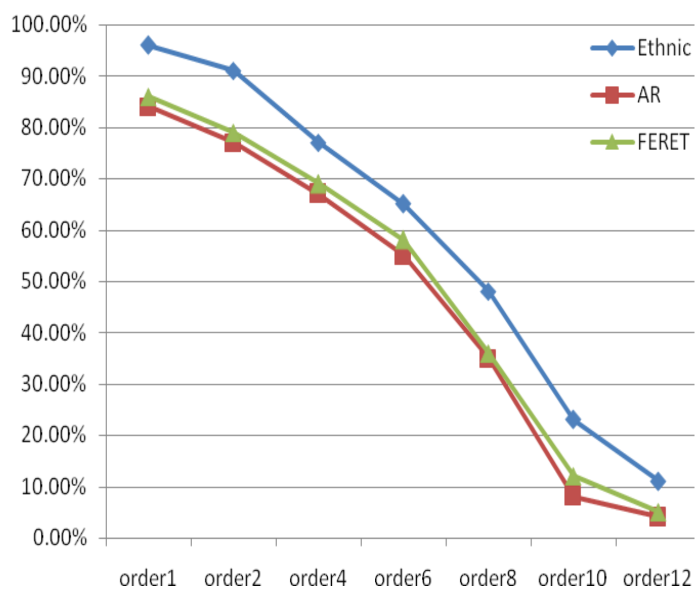

Figure 7. Recognition Rate for Various Order

In next experiment, the precision of proposed algorithm was achieved for first rank of different orders without using order comparator. Results are shown in Fig.8. The features of men and women in ethnic database show their effect in this state too. Comparing between Fig.7 and Fig.8, indicate that order comparator increases the accuracy.

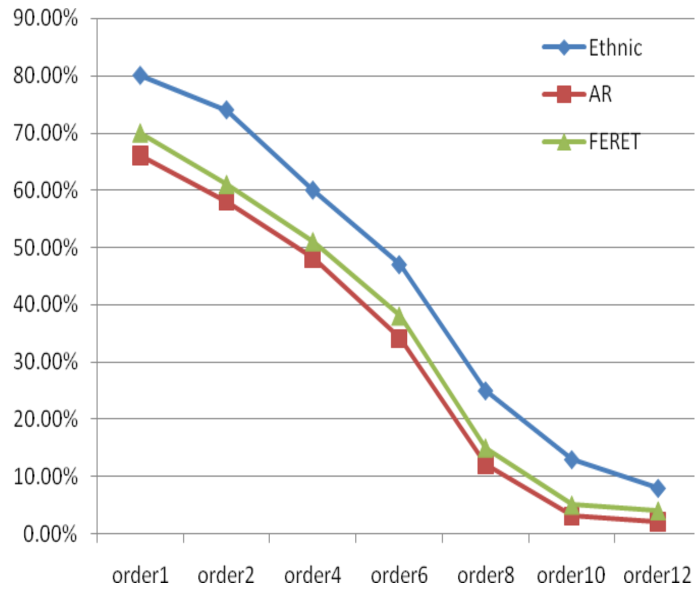

Figure 8. Recognition Rate without Order Comparator

In another experiment, the accuracy for various ranks of different orders was calculated (Table II). According to results in Table II, the precision will be maximum at first rank (*p=0*) of order1, therefore we used this state in all experiments.

Table 2. Rates for Various Rank of Different Orders

Rank	Order	Database		
		Ethnic	AR	FERET
p=0 q=1	1	96.0%	84.0%	86.0%
p=1 q=0	1	87.0%	79.0%	80.0%
p=0 q=2	2	86.0%	80.0%	82.0%
p=1 q=1	2	83.0%	77.0%	78.0%
p=2 q=0	2	80.0%	73.0%	75.0%
p=0 q=4	4	80.0%	73.0%	75.0%
p=1 q=3	4	77.0%	70.0%	73.0%
p=2 q=2	4	72.0%	63.0%	85.0%
p=3 q=1	4	67.0%	58.0%	61.0%
p=4 q=0	4	61.0%	50.0%	51.0%
p=0 q=6	6	71.0%	65.0%	67.0%
p=1 q=5	6	66.0%	56.0%	59.0%
p=2 q=4	6	60.0%	49.0%	52.0%
p=3 q=3	6	53.0%	42.0%	44.0%
p=4 q=2	6	46.0%	35.0%	38.0%
p=5 q=1	6	38.0%	27.0%	28.0%
p=6 q=0	6	29.0%	16.0%	19.0%

To evaluate the results of each moment separately (without fuzzy system), we used the proposed method based on single moment mode for recognition of input image. The results are shown in Table III. According to this Table, in single moment state, precision is worse than fuzzy combination mode. In fact, one of moments can recognize faces that one of two other moment maybe can't; therefore the combination of them is useful way for elimination of unrecognized face.

Table 3. Rates for Different Moments Separately

	Ethnic	AR	FERET
CM	86.0%	74.0%	77.0%
GM	83.0%	72.0%	74.0%
LM	91.0%	79.0%	82.0%

In final experiment we tested the proposed algorithm using AR images with partial occlusion, (100 images for glass and 100 images for scarf), Fig.9. In this state, the input test image has an occlusion but the database images haven't. This experiment led to 78% and 70% accuracy for glass and scarf occlusion, respectively. These results show that the proposed method has acceptable outcome for partial occlusion.

Figure 9. Partial Occlusion

Table IV, shows a comparing between the proposed face recognition method and the other methods dealing with the one sample problem.

Table IV. Comparing between Proposed Method and Other Methods

Method	Database	No. of Person	Recognition rate	Reference
Local probabilistic subspace	AR	100	82%	[14]
2DPCA	AR	100	74%	[15]
(PC)2A	FERET	200	83.5%	[16]
E(PC)2A	FERET	200	85.5%	[17]
SVD Perturbation	FERET	200	85%	[18]
Modular FLDA	FERET	200	86.5%	[19]
Component LDA	FERET	70	78.5%	[20]
Discriminant PCA	FERET	256	71.8%	[21]
Proposed	AR	100	84%	
Proposed	FERET	100	86 %	
Proposed	Ethnic	100	96%	

5. Conclusion

In this paper a novel face recognition algorithm based on moments feature vectors was proposed. Unlike previous efforts which try to recognize the input image via a training process, our algorithm was based on single image per person that tackles the need for any training process. The proposed face recognition algorithm was evaluated on 100 images from ethnic, AR and FERET databases. The results showed 96%, 86% and 84% accuracy for ethnic, FERET and AR respectively. It means that some features in the ethnic database, Hijab for women and beard and mustache for men, cause to reduce errors between men and women in recognition process and consequently we will have higher precision.

References

[1] X. Tan, S. Chen, Z.H. Zhou, F. Zhang, "Face recognition from a single image per person: a survay", Pattern Recognition, **(2006)**, pp. 1725 – 1745.

[2] J. Wang, K.N. Plataniotis, J. Lu, A.N. Venetsanopoulos, " On solving the face recognition problem with one training sample per subject", Pattern Recognition, **(2006)**, pp. 1746 – 1762.

[3] H. Jia, A.M. Martinez, "Support Vector Machines in face recognition with occlusions", IEEE conference on Computer Vision and Pattern Recognition, CVPR, **(2009)**.

[4] Z. Lihong, S. Ying, Z. Yushi, Z. Cheng, Z. Yi, "Face recognition based on multi-class SVM", Chinese Control and Decision Conference, CCDC, **(2009)**.

[5] V.T.L. Huong, D.C. Park, Y, Lee "Centroid neural network for face recognition", International Joint Conference On Neural Networks, IJCNN, **(2009)**.

[6] R. Tiwari, A. Shukla, C. Prakash, D. Sharma, R. Kumar, S. Sharma, "Face Recognition using morphological method", IEEE International Advance Computing Conference, IACC, **(2009)**.

[7] C.H. The, R.T. Chin, "On image analysis by the method of moments", IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI, **(1988)**.

[8] A.M. Martinez and R. Benavente, "The AR Face Database", CVC Technical Report #24, **(1998)** June.

[9] P.J. Philips, H. Moon, S.A. Rizvi, P.J. Rauss, "The FERET Evaluation Methodology for Face Recognition Algorithms", IEEE Trans. Pattern Analysis and Machine Intelligence, PAMI, **(2000)**.

[10] http://rvl1.ecn.purdue.edu/~aleix/ar.html

[11] http://face.nist.gov/colorferet/request.html

[12] R. Courant, D. Hilbert, "Methods of mathematical physics", vol. 1, New York: Interscience, **(1953)**.

[13] Perlibakas, "Distance measures for PCA-based face recognition", Pattern Recognition Letters, **(2004)**, pp. 711-724.

[14] A.M. Martinez, "Recognizing imprecisely localized, partially occluded, and expression variant faces from a single samples per class", IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI, **(2002)**.

[15] J. Yang, D. Zhang, A. F. Frangi, "Two dimentional PCA: a new approach to appearance-based face representation and recognition", IEEE Transactios on Pattern Analysis and Mahine Intelligence, PAMI, **(2004)**.

[16] J. Wu, Z.H. Zhou, "Face recognition with one training image per person", Pattern Recognition Letters, **(2002)**, pp. 1711-1719.

[17] S.C. Chen, D.Q. Zhang, Z.H. Zhou, "Enhanced (PC)2A for face recognition with one training image per person", Pattern Recognition Letters, **(2004)**, pp.1173-1181.

[18] D.Q. Zhang, S.C. Chen, Z.H. Zhou, "A new face recognition method based on SVD perturbation for single example image per person", Appl. Math. Comp, **(2005)**, pp.895-907,.

[19] S.C. Chen, J. Liu, Z.H. Zhou, "Making FLDA applicable to face recognition with one sample per person", Pattern Recognition, **(2004)**, pp.1553-1555.

[20] J. Huang, P.C. Yuen, W.S. Chen, J.H. Lai, "Component-based LDA method for face recognition with one training sample", AMFG, **(2003)**.

[21] J. Wang, K.N. Plataniotis, A.N. Venetsanopoulos, "Selecting discriminant eigenfaces for face recognition", Pattern Recognition Letters, **(2005)**, pp.1470-1482.

Authors

Rohollah Akbari received his BSc (2004) and MSc (2009) in electronic engineering from Azad university of Qazvin, Iran. His research interests include Digital Image Processing, Computer Vision and Pattern Recognition.

Saeed Mozaffari received his B.Sc. and M.Sc. degrees in Electrical Engineering from Amirkabir University of Technology, Theran, Iran in 1999 and 2001, respectively. In 2006, he attended Technical University of Braunschweig in Germany as sabbatical leave to finalize his PhD thesis. After obtaining his PhD from Amirkabir University of Technology in 2007, Dr. Mozaffari joined Semnan University in Iran.

His research interests include Digital Image Processing, Computer Vision, Pattern Recognition, and Document analysis.