International Journal of Modern Engineering Research (IJMER)
www.ijmer.com Vol.2, Issue.1, pp-060-065 ISSN: 2249-6645

An Efficient Illumination Normalization Method with Fuzzy LDA Feature Extractor for Face Recognition

Behzad Bozorgtabar[1], Hamed Azami[2]
(Department of Electrical Engineering / Iran University of Science and Technology, Iran)

ABSTRACT
The most significant practical challenge for face recognition is perhaps variability in lighting intensity. In this paper, we developed a face recognition which is insensitive to large variation in illumination. Normalization including two steps, first we used Histogram truncation as a pre-processing step and then we implemented Homomorphic filter. The main idea is that, achieving illumination invariance causes to simplify feature extraction module and increases recognition rate. Then we utilized Fuzzy Linear Discriminant Analysis (FLDA) in feature extraction stage which showed a good discriminating ability compared to other methods while classification is performed using three classification methods : Nearest Neighbour classifier , Support Vector Machines (SVM) and Feedforward Neural Network(FFNN).The experiments were performed on the ORL (Olivetti Research Laboratory) and Yale face image databases and the results show the present method with SVM classifier outweighs other techniques applied on the same database and reported in literature.

***Keywords* - Face Recognition, Homomorphic filter, Nearest Neighbour, Fuzzy LDA, SVM, FFNN**

I. INTRODUCTION
Face recognition has become one of the most active research areas of pattern recognition since the early 1990s, and has attracted substantial research efforts from the areas of computer vision, bio-informatics and machine learning.
Illumination is considered one of the most difficult tasks for face recognition. The illumination setup in which recognition is performed is in most cases impractical to control, its physics difficult to accurately model and face appearance differences due to changing illumination are often larger than those differences between individuals. Reliable techniques for recognition under more extreme variations caused by pose, expression, occlusion or illumination is highly nonlinear, have proven elusive [1].

In this paper, we outline a hybrid technique for illumination normalization, after the Histogram truncation was applied to input face images, the Homomorphic filter was used for normalization. The face recognition involves two major steps. In the first step, some features of the image are extracted. In the second step, on the basis of the extracted features the classification is performed.

Fuzzy LDA (Fuzzy Fisherface) recently, was proposed for feature extraction and face recognition [2]. Fuzzy LDA computes fuzzy within-class scatter matrix and between-class scatter matrix by incorporating class membership of the binary labeled faces (patterns).

Finally extracted features were considered as inputs to classifiers. In this paper well-known classifiers including Nearest Neighbor, SVM and Feedforward Neural Networks were employed as classification.

Then rest of this paper is as followed. Our proposed method is initiated in second section then Fuzzy LDA is introduced in third section. Classification, experimental results on both ORL and Yale datasets, and Conclusion are depicted in continue.

II. ILLUMINATION NORMALIZATION TECHNIQUE
In this stage, in order to boost the result of normalization, we first truncated a specified percentage of the lower and upper ends of an image histogram.

In fact, several studies have shown that histogram remapping in conjunction with photometric normalization techniques results in better face recognition performance than using photometric normalization techniques on their own.

In the next step, Homomorphic filter as a renowned illumination reflectance was used. And then filtered face image is considered as input of feature extraction module.

A. Homomorphic Filter
Homomorphic filtering (HOMO) is a well known normalization technique, which improves the

pearance of an image by contrast enhancement and gray-level range compression.

Consider an image, $f(x, y)$, which can be stated as the product of the illumination $i(x, y)$, and the reflectance component $r(x, y)$ as follows [3]:

$$f(x, y) = i(x, y).\ r(x, y) \quad (1)$$

Then input image is transformed in to the logarithm domain in order to achieve frequency components of the illumination and reflectance separately:

$$z(x, y) = \ln f(x, y) \quad (2)$$

$$= \ln i(x, y) + \ln r(x, y)$$

Then:

$$\{ z(x, y) \} = \mathfrak{F} \{ \ln f(x, y)\}$$

$$= \mathfrak{F} \{ \ln i(x, y)\} + \mathfrak{F}\{ \ln r(x, y)\}$$

Or:

$$Z(u, v) = F_i(u, v) + F_r(u, v)$$

Where $F_i(u, v)$ and $F_r(u, v)$, in equation (2) are the Fourier transforms of the term defined.

The Fourier transform of the product of the $Z(u, v)$ and filter function $H(u, v)$ can be expressed as:

$$S(u, v) = H(u, v).\ Z(u, v) \quad (3)$$

$$= H(u, v).\ F_i(u, v) + H(u, v).\ F_r(u, v)$$

In the spatial domain:

$$s(x, y) = \mathfrak{F}^{-1}\{ S(u, v)\}$$

$$= \mathfrak{F}^{-1}\{H(u, v).\ F_i(u, v) + H(u, v).\ F_r(u, v)\}$$

Finally by letting

$$i(x, y) = \mathfrak{F}^{-1}\{ H(u, v).\ F_i(u, v) \} \quad (4)$$

$$(x, y) = \mathfrak{F}^{-1}\{ H(u, v).\ F_r(u, v) \}$$

the equation becomes:

$$s(x, y) = i(x, y) + r(x, y) \quad (5)$$

$$g(x, y) = e^{s(x,y)}$$

$$g(x, y) = e^{i(x,y)} + e^{r(x,y)}$$

$$g(x, y) = i_0(x,y) + r_0(x, y)$$

Where i_0 and r_0 are the illumination and the reflectance components of the output images. After $z(x, y)$ is transformed into the frequency domain, the high frequency components are emphasized and the low-frequency components are reduced. As a final step the image is transformed back into the spatial domain by applying the inverse Fourier transform and taking the exponential of the result.

This method is based on a special case of a class of systems known as Homomorphic system. The filter transform function $H(u, v)$ is known as the Homomorphic filter[4] .

III. FUZZY LDA (FLDA)

Fuzzy LDA, which also was called Fuzzy Fisher Face method, is considered to solve binary classification problems. In conventional LDA approach, every vector is supposed to have a crisp membership. But this does not take into account the resemblance of images belonging to different classes, which occurs under varying conditions. In FLDA, each vector is assigned the membership grades of every class based upon the class label of its k nearest neighbours. This Fuzzy k-nearest neighbour is utilized to evaluate the membership grades of all the vectors [5].

The membership degree to class i for j^{th} pattern is obtained from following equation[5]:

$$u_{ij} = \begin{cases} 0.51 + 0.49\left(n_{ij}/k\right) & i, j\ belong\ \ to\ \ the\ \ same\ \ class \\ 0.49\left(n_{ij}/k\right) & otherwise \end{cases} \quad (6)$$

In the above expression n_{ij} stands for the number of the neighbors of the j^{th} data (pattern) that belong to the i^{th} class. As usual, u_{ij} satisfies two obvious properties:

$$\sum_{i=1}^{C} u_{ij} = 1 \quad (7)$$

$$0 < \sum_{j=1}^{N} u_{ij} < N \quad (8)$$

Therefore, the fuzzy membership matrix U can be achieved with result of FKNN.

$$U = [u_{ij}]\, i = 1,2,..., c \quad j = 1,2,..., N \quad (9)$$

The results of the FKNN are used in the computations of the statistical properties of the patterns.

Taking in to account the fuzzy membership degree, the mean vector of each class is [6]:

$$m_i = \frac{\sum_{j=1}^{N} u_{ij} x_j}{\sum_{j=1}^{N} u_{ij}} \tag{10}$$

Then, the membership degree of each sample (contribution to each class) should be considered and the corresponding fuzzy within-class scatter matrix and fuzzy between-class scatter matrix can be redefined as follow [7]:

$$FS_W = \sum_{i=1}^{c} \sum_{x_j \in w_i} u_{ij} (x_j - m_i)(x_j - m_i)^T \tag{11}$$

$$FS_b = \sum_{i=1}^{c} \sum_{j=1_i}^{N} u_{ij} (m_i - \bar{X})(m_i - \bar{X})^T \tag{12}$$

Where $\bar{X}$, is the mean of all samples. So, all scatter matrices with fuzzy set theory are redefined and the contribution of each sample is incorporated.

Our optimal fuzzy projection W_{F-LDA} follows the expression:

$$W_{F-LDA} = \arg\max_w \frac{|W^T FS_B W|}{|W^T FS_W W|} \tag{13}$$

It is difficult to directly calculate W_{F-LDA} because that FS_W is often singular [6]. For tackle this problem, PCA is used as a dimension reduction step and thus the final transformation is given by the following matrix,

$$W^T = W_{F-LDA}{}^{\mathrm{T}} W_{PCA}{}^{\mathrm{T}} \tag{14}$$

IV. Classification

A. Nearest Neighbour Classifier

After evaluating feature vectors by FLDA, test images are projected on feature space and the distances to the training images are computed using nearest neighbour algorithm for the purpose of classification as follows [8]:

For two images i and j, let $f^{(i)}$ and $f^{(j)}$ representing the corresponding feature vectors, the distance d_{ij} between the two patterns in the feature space is defined as:

$$d_{ij} = \sqrt{\sum_n \left(\frac{f_{(n)}^{(i)} - f_{(n)}^{(j)}}{\alpha(f_n)} \right)^2} \tag{15}$$

Where $f_n^{(i)}$ is the *nth* element of the feature vector *i* while the term $\alpha(f_n)$ is the standard deviation of the *nth* element over the entire database and is used to normalize the individual feature components. Finally, a test image *j* is assigned to image *i* in a database with the smallest corresponding distance d_{ij} .

B. Feedforward Neural Networks (FFNN)

FFNN is suitable structure for nonlinear separable input data. In FFNN model the neurons are organized in the form of layers. The neurons in a layer get input from the previous layer and feed their output to the next layer. In this type of networks connections to the neurons in the same or previous layers are not permitted. Fig 1 shows the architecture of the system for face classification [9-10].

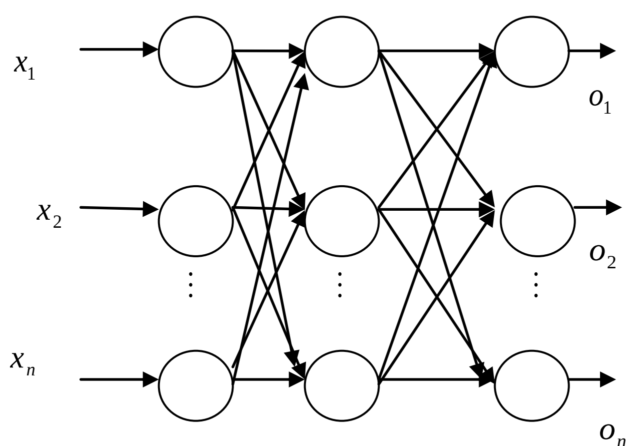

Fig.1. Architecture of FKNN for classification

In this experiment the number of nodes in hidden layer is set to 15. A large neural network for all people in the database was implemented. After calculating the features, the feature projection vectors are calculated for the faces in the database. These feature projection vectors are used as inputs to train the neural network. Fig 2 illustrates the schematic diagram for the NN training phase.

C. Support Vector Machine (SVM)

SVM is a binary classification method that intends to find the optimal linear/nonlinear decision surface based on the concept of structural risk minimization. The decision surface is a weighted representation of the elements of training set. The elements on the decision surface are defined by a set of support vectors which characterizes the boundary between two (or more) classes [11]. The problem of multi-class is solved by combining multiple two class SVMs. We select the one-versus-the-rest approach that constructs SVMs which the train k^{th} model chooses the k^{th} class as the positive examples and the remaining $(k-1)$ classes as the negative examples. Comparison with one-versus-one, it significantly needs less training time. At last, indexed SVM classifier is learned through quadratic programming in order to find the class's boundaries with maximum margins. This technique helps to find the accurate relations between nearest similarity faces.

V. Simulation and Results

A. ORL Face Database

The ORL database consists of 40 groups, each containing ten 112×92 gray scale images of a single subject [12]. Each subject's images differ in lighting, facial expression, details (i.e. glasses/no glasses) and even sliding. Some of the database's images are illustrated in Fig 3.

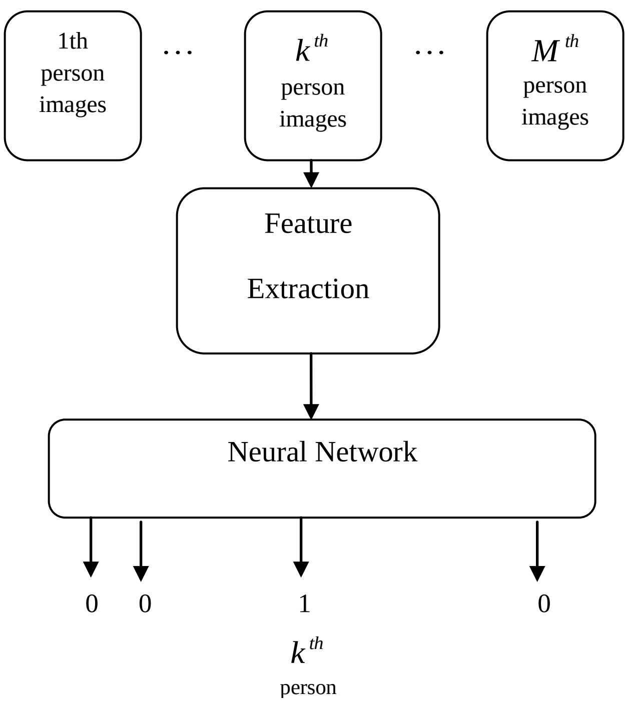

Fig.2. Training stage for Neural Network

The ORL database consists of 40 groups, each containing ten 112×92 gray scale images of a single subject. Each subject's images differ in lighting, facial expression, details (i.e. glasses/no glasses) and even sliding. Some of the database's images are illustrated in Fig 3.

Fig 4 shows an original image from ORL database and its histogram respectively. This image is chosen specifically because it had led to misclassification in many feature extraction methods. Being taken under ambient lighting in a neutral facial expression and the person wore glasses, the images of this class lead to increase in error rate.

In the next step,the Homomorphic filter was applied to the selected image for normalization. The filtered image and its histogram are displayed by Fig5.

Initially we implemented the Histogram truncation, in this step the lower and upper ends of an image histogram that must be truncated, were set to 20 percent and 60 percent respectively.

Then Homomorphic filter was used, the performance of this filter rely on its parameters. We set the cut-off frequency of the filter to 0.5 and second order of the modified Butterworth style filter is used. In the next step, we shortened half of upper ends of final histogram.

After preprocessing step, FLDA was applied in order to extract features. Then described classifiers are implemented.

Fig.3. Samples of ORL face database

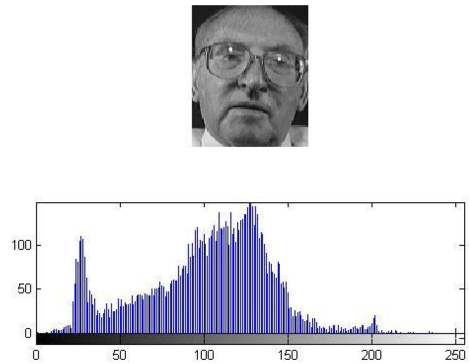

Fig.4.Original image and the corresponding histogram

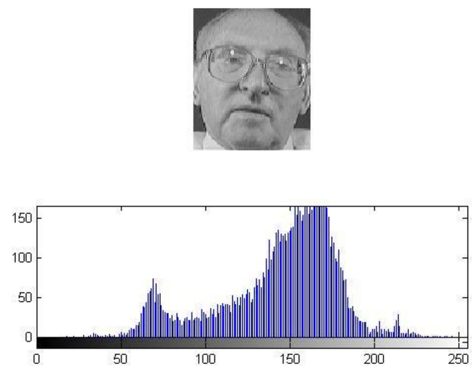

Fig.5.Filtered image and the corresponding histogram

Two set of images were created from the ORL face database; For the Five-to-Five dataset, five random images of each group were selected for training while the others were used for testing. For the Leave-One-Out set, 9 images were used for training and the remaining image was kept for validation.

Table 1 shows comparison among different methods in Five-to Five set that simulation results show SVM classifier with proposed method has a better performance compared to other classifiers.

Table 1. Comparison of recognition rates of different classifiers based on various feature extractors for ORL face database

	Nearst Neighbour	SVM	FFNN
PCA	88%	90%	89%
LDA	90%	92%	91%
FLDA	94%	95%	92%
2D-PCA	93%	94.5%	93%
Proposed	95%	96.5%	94.5%

Table2 illustrates recognition rates of depicted methods with nearest neighbour classifier for two sets.

Table2. Comparison of recognition rates of different methods for two sets

	Five-to-Five	Leave one -out
PCA	88%	89.%
LDA	90%	91%
FLDA	94%	95%
2DPCA	93%	94.%
Proposed	95%	96%

B. Yale Face Database

The Yale face database contains 165 images of 15 individuals (each person providing 11 different images) under various facial expressions and lighting conditions [13]. Fig 6 shows sample images of one person.

Similar procedure was done for Yale face database. In this set 6 images were used for training from each class and remaining images were employed for test module. As far as recognition rate is concerned proposed method outranks others with 96.5 and 95.5 percent for SVM and two other classifiers respectively. In addition the outcomes of Feedforward Neural Networks and Nearest Neighbour are close to each other. The results were shown in Table 3.

Fig.6. Samples of Yale face database

Table3. Comparison of recognition rates of different classifiers based on various feature extractors for Yale face database

	Nearest Neighbour	SVM	FFNN
PCA	89%	90%	90%
LDA	91%	93%	92%
FLDA	93.5%	94%	91%
2D-PCA	94%	95%	93.5%
Proposed	95.5%	96%	95.5%

VI. Conclusion

In this paper, the Face Recognition problem was addressed by improved method based on modified Homomorphic filter, which is insensitive to large variation in illumination.

Homomorphic filter is a celebrated normalization technique which was ignored in face recognition. In continue Fuzzy LDA (FLDA) was used that compared to other feature extractors, it had a good ability in discriminating of classes.

Finally proposed method in collaboration with appropriate classifiers was used which the result showed proposed method with SVM classifier had a best performance.

References

[1] Y A. Georghiades, P. Belhumeur, and D. Kriegman,, From few to many: Illumination cone models for Face Recognition under variable lighting and pose, *IEEE Transactions on Pattern Analysis and Machine Intelligence, 23(6),* 2001, 643-660.

[2] Kw K C, Pedry W, Face recognition using a fuzzy fisher classifier, *Pattern Recognition, 38(10),* 2005, 1717-1732.

[3] Thammizharasi,A.M.E, Performance Analysis Of Face Recognition By Combining Multiscale Techniques And Homomorphic filter using Fuzzy k-nearest neighbour classifier, *Proc. IEEE Conf. on Communication Control and Computing Technologies (ICCCCI'10)*, 2010, 643-650.

[4] N. Ahmed Surobhi , Md. Ruhul Amin, Employment of Modified Homomorphic filters in Medical Imaging, *International University Journal of science and Technology in Daffodil, 1(1),* 2006.

[5] M.Keller, M.R.Gray, J.A.Givern, A Fuzzy K Nearest Neighbor Classifier Algorithm, *IEEE Transactions on Systems, Man and Cybernetics, 15(4),* 1985,580-585.

[6] W. Yang, Hui Yan, J. Wang, J. Yang, Face Recognition using Complete Fuzzy LDA, *Proc. 19th International Conf. on Pattern Recognition*, ICPR,2008, 1-4.

[7] X Song,Y Zheng, A complete Fuzzy Discriminant Analysis Approach for Face Recognition, *Applied Soft Computing*, 2010,208-214.

[8] Peter N. Belhumeur, Joao P. Hespanha, David J. Kriegman, Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection, *IEEE Transactions on Pattern Analysis and Machine Intelligence, 19(7),* 1997.

[9] A. Eleyan , H. Demirel, Face recognition system Based on PCA and Feedforward Neural Networks, *Proc. Computational Intelligence and Bioinspired Systems*, Barcelona, Spain, 2005, 935-942.

[10] Lawrence, S., Giles, C. L., Tsoi, A. C., Back, A. D., Face Recognition: A Convolutional Neural-Network Approach, *IEEE Transactions on Neural Networks, 8(1),* 1997.

[11] J. Huang, V. Blanz and B. Heisele, Face recognition using component-based SVM. Classification and morphable models, *Lecture Notes in Computer Science, 23(88),* 2002, 334-341.

[12]ORL, "The Database of Faces," 2011. http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatase.html.

[13]Yale, "The Database of Faces," 2011. cvc.**yale**.edu/projects/**yalefaces**/**yalefaces**.html