

A NOVEL METHOD OF AVERAGE FILTERING FOR REMOVING NOISE AND FACE RECOGNITION

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ABSTRACT: *Face recognition is new and difficult which requires great effort and determination due to the Wide variety of faces, complexity of noises and image backgrounds. In this paper, we propose an Average Filtering based novel method for face recognition in cluttered and noisy images. It is imperative that computational researchers know of the key findings from experimental studies of face recognition by human. These findings provide insights into the nature of starting symbol to begin that the human visual system relies upon for achieving its great deal of performance and serve as the building blocks for efforts to artificially emulate these abilities. In this paper, we are presenting what we believe are various basic results, with implications for the computational design systems. The aim of our proposed work of average filtering based method for face recognition is to improve the recognition accuracy. We use AT&T face database and experiments on it are performed to demonstrate the effectiveness of the proposed method.*

KEYWORDS: Face Recognition, Principal Component Analysis, Linear Discriminant Analysis, Laplacianfaces, Average Filter, Smooth Mean Filter, Feature Extraction, Eigenfaces, Fisherfaces.

INTRODUCTION

The high precision face recognition is based on high recognition rate of faces and this is important for many applications of security, management and services. To increase the face recognition rate, face recognition algorithm have to minimize the disturbances of facial poses and remove the noise in face images.

Main aspect of the proposed approach is that while eigenfaces method aims to preserve the global structure of the image space, the fisherfaces method aims to preserve the discriminating information, laplacianfaces method aims to preserve the local structure of image space[1] and PCA,LDA and LS-CLFDA methods aim to solve the problem of dimensionality reduction[2]; Average Filtering based Face Recognition method aims to remove the noise before recognition phase.

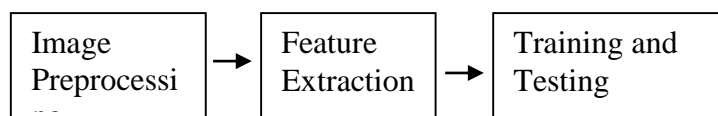


Figure1. Basic block of a face recognition system

Image Preprocessing

In the initial phase, gray scale is used as input and resized to the required size; noise is removed by smooth mean filter. Preprocessing methods use a small neighborhood of a pixel in an input

image to get a new brightness value in the output image. Such a pre-processing operation is also called filtration. Local pre-processing methods can be divided into the two groups according to the goal of the processing:

1. Smoothing suppresses noise or other small fluctuations in the image; equivalent to the suppression of high frequencies in the frequency domain. Unfortunately, a smoothing also blurs all sharp edges that bear important information about the image.
2. Gradient operators are based on local derivatives of the image functions. Derivatives are bigger at locations of the image where the image function undergoes rapid changes. The aim of gradient operators is to indicate such locations in the image. Gradient operator suppresses low frequencies in the frequency domain (i.e. they act as high-pass filters). The noise is often a high frequency in nature; unfortunately, if the gradient operator is applied to an image the noise level increases simultaneously.
3. Clearly, smoothing and gradient operators have conflicting aims. Some preprocessing algorithms solve this problem and permit smoothing and edge enhancement simultaneously.

Another classification of the local preprocessing methods is according to the transformation properties:

- Linear operations calculate the resulting value in the output image pixel $g(i,j)$ used as a linear combination of brightness in a local neighborhood of pixel $f(i,j)$ in a input image. The contribution of the pixels in the neighborhood is weighted by coefficients h .

$$f(i,j) = \sum \sum h(i-m,j-n) g(m,n) \quad \dots\dots(1.1)$$

$$(m,n) \in O$$

The above equation is identical to discrete convolution with the kernel h that is called a convolution mask.

- The rectangular neighborhoods O are often used with an odd number of pixels in rows and columns, enabling the specification of the central pixel of the neighborhood.
- A local preprocessing method typically use very little a priori knowledge about the image contents, which is very difficult to infer this knowledge while an image is processed as the known neighborhood O of the processed pixel is small.
- The choice of the local transformation, shape and size of the neighborhood O depends strongly on the size of objects in the processed image. If objects are rather large then an image can be enhanced by smoothing of small degradations.

Feature Extraction: The purpose of the feature extraction is to extract the feature or information which represents the face and reduce the computation time and improve the recognition rate. In feature extraction facial features are extracted using Average Filtering method. The first step in image analysis is to extract the features of the image. Feature extraction is a method by which the relevant information related to digital image is extracted. The level to which this extracting is carried depends on the problem being solved. Feature extraction is typically used to collect the features of objects in images. Sometime we need to read the image correctly and identify the content of the image. In the sense analysis or any visual pattern recognition process, the camera accepts a picture of the scene and passes picture to feature extractor. Thus objective of a feature extractor is data reduction by measuring certain

features or properties which distinguish objects or their parts. Usually, feature extraction is associated with another technique known as feature selection. The objective of feature selection and feature extraction techniques is to reduce this dimensionality. During this process, the salient features are essential for the recognition is retained. As a result, classification methodologies may implement in space with vastly reduced dimension and therefore it requires reasonable time.

Training and Testing: Training basically involves feeding training samples as input through a proposed method. Testing image is used as a sample image which has to recognize from the trained images. In this section and the next section, we conduct comprehensive experiments on large-scale face databases to verify the performance of our algorithm and system. We first test on the largest public face database available that is suitable for testing our algorithm, the AT&T. One shortcoming of the AT&T face database for our purposes is that there is no separate set of test images taken under natural illuminations; we are left to choose which sets of images to use for testing and training. To challenge our algorithm, we choose only a small set of illuminations for the training set, yet we include all illuminations in the testing set. In the following section, we will test our algorithm on a face dataset that is collected by our own system. The goal for that experiment will be to show that with a sufficient set of training illuminations for each subject, our algorithm indeed works stably and robustly with practical illumination, misalignment, pose, and occlusion, as already indicated by our experiment shown in Figure 7. AT&T provides the most extensive test set among public datasets. This database contains images of 400 subjects across simultaneous variation in pose, expression, and illumination. Of these 400 subjects, we use all of the 40 subjects present in Session 1 as the training set. The remaining 360 subjects are treated as testing images. The dataset is challenging due to the large number of subjects, and due to natural variation in subject appearance over time. Table 1 shows the result of our algorithm on each of the 4 testing sessions. Our algorithm achieves recognition rates above 97% for all four sessions.

Gaussian Noise and its influence on image: Gaussian noise is a general kind of a noise which can be effect the visualization or clarification of the image, for better recognition of image we have to remove this noise from image. Gaussian noise arises in an image due to factors such as sensor noise, circuit noise, poor illumination and high temperature. The probability Density Function (PDF) of Gaussian noise is given by the expression:

$$P(z) = \frac{e^{-(z-\mu)^2/2\sigma^2}}{\sqrt{2\pi}\sigma}$$

Where:

Z = Gray level

μ = Mean of average value of z

σ = Standard Deviation

σ^2 = Variance

A special case is white Gaussian noise, in which the values at any couple of times are identically distributed and statistically independent (hence uncorrelated). In communication channel testing and modeling, Gaussian noise is used as additive white noise to generate additive white Gaussian noise. In communication channels like computer networking and telecommunication, can be affected by wide-band Gaussian noise coming from many natural sources, such as the thermal vibrations of atoms in conductors (referred to as thermal noise or

Johnson-Nyquist noise), shot noise, black body radiation from the earth and other warm objects, and from celestial sources such as the Sun.

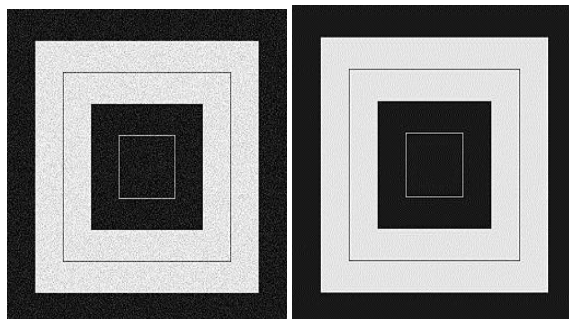


Figure 2: image without Gaussian noise and with Gaussian noise

Principal sources of Gaussian noise in digital images arise during appropriation e.g. sensor noise caused by poor illumination and/or high temperature, transmission e.g. electronic circuitry noise. In a digital image processing Gaussian noise can be reduced using a spatial filter, when smoothing the image, an unsuitable outcome may result in blurring of fine-scaled image edges and details because they also correspond to blocked the high frequency. The conventional spatial filtering techniques for removal include: mean (convolution or average) filtering, median filtering and Gaussian smoothing.

OVERVIEW OF PREVIOUS WORK:

There are several researches which are done in previous decades, some of them are:

- Xiaofei He, Yuxiao Hu, Shuicheng Yan, Partha Niyogi and Hong-Jiang Zhang[1] in 2005 introduced Laplacianfaces for face recognition having better performance on the MSRA database over the approaches- Eigenfaces and Fisherfaces.
- Neerja and Ekta Walia[7] in 2008, proposed improved fast PCA Algorithm to improve the performance of traditional methods. This method is simple to implement and fast in computing. So far they have tested this approach on a relatively medium sized and clean database only.
- Kolhadai Yesu, Kaveri Chetia, Himadri Jyoti Chakravorty, Prantik Bhuyan, Kaustubh Bhattacharyya proposed “Innovative Feature Extraction Method For Artificial Neural Network Based Face Recognition” [6], in this work they used Artificial Neural Network with back propagation algorithm and they found this algorithm is to be efficient for recognition faces. This paper has a problem of noisy images which can reduce the efficiency of ANN method in 2012.
- Dong-Ju Kim, Sang-Heon Lee and Myuong-Kyu Sohn worked on “Face Recognition via Local Directional Pattern” [5] at this paper they worked for illumination invariant face recognition via LDP image, it has an advantage that illumination effects can be degraded by LDP descriptor and 2D-PCA is also more robust against illumination variation than global features.
- To improve the heartiness of 2DPCA and BDPCA, Wankou Yang, Changyin Sun, Lei Zhang, Karl Ricanek[4] in 2010; proposed the Laplacian BDPCA at which first the

Laplacian row total scatter matrix and Laplacian column total scatter matrix were defined then the projectors were obtained by calculating the eigen vectors of the Laplacian row and column total scatter matrices, finally the image matrix was projected onto the projectors to extract the LBDPCA features.

To solve the challenge of dimensionality reduction and improve the accuracy of recognizing the faces of Local Fisher Discriminant Analysis; Hong Huang, Hailiang Feng, Chengyu Feng introduced Complete Local Fisher Discriminant Analysis with Laplacian Score ranking for face recognition[2] in 2012.

Haitao Gan[3] in 2014 introduced a semi-supervised learning algorithm, called Laplacian Regularized KMSE; who construct a nearest neighbor graph to exploit the manifold structure and Laplacian Regularized term to smooth the labels of labeled and unlabeled examples along the geodesics on the manifold which gives effectiveness results on simple KMSE method.

PROPOSED METHOD

The high precision face recognition is depends on high recognition rate of faces and this is important for many applications of security, management and services. To increase the face recognition rate, face recognition algorithm have to minimize the disturbances of facial poses and remove the noise in face images. In our work, we proposed a novel method using smooth mean filter and average filter for face recognition. In this work we use smooth filter for removing noise of both image sets testing and training and average filter is used to obtain a new image matrix of testing and training images which is later be used for identification and recognition of faces. In this method firstly we fetch the gray scale image from a testing database or from any input devises. Image may have various noises and artifacts so we apply smooth mean filter of size 3×3 , to remove the noise or to blur the sharp edges. The smooth mean filter remove the Gaussian noise and blur the sharp edges and provide a noise free facial image which is used in average filter to generate the image for matching. In the matching phase we compare the total difference of testing image and training image with the threshold value of training dataset, if the total difference is equal or less than the threshold then image is matched otherwise image will not be matched.

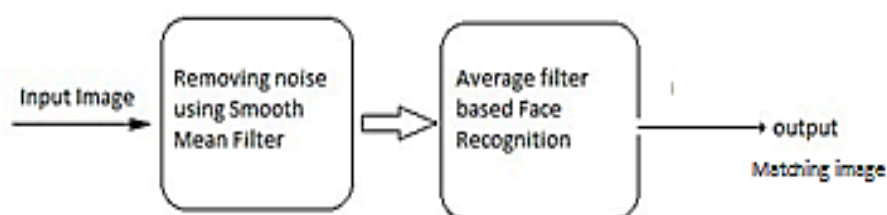


Figure 3: Basic structural diagram of proposed work

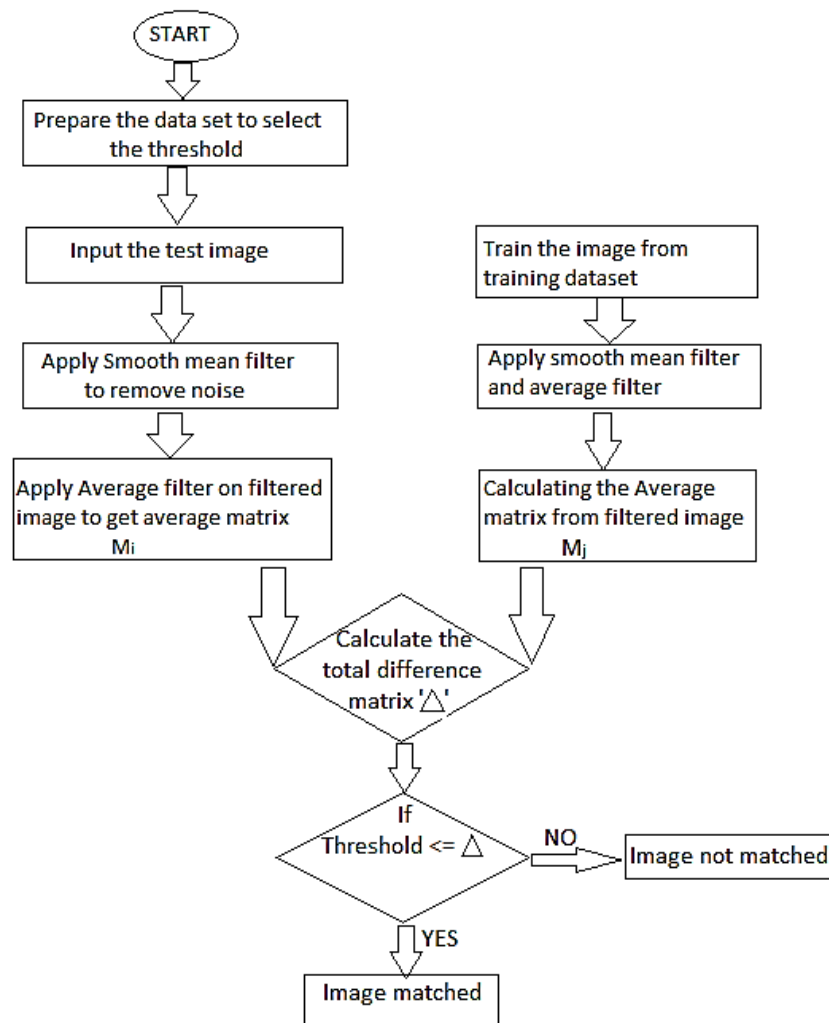


Figure 4: Flowchart of proposed system

We begin with a description of the Smooth Mean Filter for removing the noise as preprocessing phase.

Smooth Mean Filter and Average filtering: Smooth mean filter is a special type of mean filter which is used to remove the noise and we used this filter in our work as a preprocessing phase to remove the noise, to eliminate the noise or blur the sharp edges. In this phase image reads pixel by pixel then reads the intensity of every pixel from 0 to 255(gray level). Smooth mean filter can be understood with the help of averaging method which is used to calculate the mean value of pixels. Averaging method for smooth mean filter is discussed below:

Averaging method: Averaging method is a filtering method to calculate the average of the pixels. It has a particular size of window to identify the value of all neighborhood pixels and their pixel value then average method calculate the average pixel value according to given window, in this work this window size is 3×3 , Assume that the noise value at each pixel is an independent random variable with standard deviation and zero mean. The result of averaging

is the average of the same n points in these images from g1 to g{n} with noise values from {1} to {n}.

$$\frac{g_1 + \dots + g_n}{n} \dots\dots\dots(2.1)$$

The second term here describes the effect of noise, a random value having a zero mean. A standard deviation of the noise can be reduced by a factor of 1 over the square root of n. Thus if 'n' number of images of the same scene is obtainable, the smoothing can be achieved by apply the Smooth Mean Filter:

$$f(i,j) = \frac{1}{n} \sum_{k=1}^n g_k(i,j) \dots\dots\dots(2.2)$$

3x3 size window for smooth mean filter:

$$h = \frac{1}{9} \begin{matrix} \boxed{1} & \boxed{1} & \boxed{1} \\ \boxed{1} & \boxed{1} & \boxed{1} \\ \boxed{1} & \boxed{1} & \boxed{1} \end{matrix}$$

In many cases only one image with noise is obtainable, and averaging is then perceived in a local neighborhood. Results are acceptable if the noise is smaller in size than the smallest objects of interest in the image.

After applying this Smooth Mean Filter, we get the new image without Gaussian noise. Brightness adjustment is done according to high gray level value and low gray level value of a particular pixel. Image with a Gaussian noise and image without Gaussian noise is shown in Figure 2.

After preprocessing phase we have to train the face images for recognition, so we use an Average Filtering method. Average filter or mean filter is windowed filter of linear class, that smoothes signal (image). The filter works as low-pass. The basic concept behind filter is for any element of the signal (image) take an average across its neighborhood. To extrapolate how that is made in practice, let's start with window idea:

1. Place a window over element.
2. Take an average: sum up elements and divide the sum by the number of elements

Consider a time series $Y_t, t = 1, \dots, N$. A symmetric (centered) moving Average filter of window length $2q+1$ is given by:

$$M_t = \sum_{j=q}^q B_j Y_{t-j} \dots\dots\dots(2.3)$$

$J = -q$

You can choose any weights b, that sum into one. To estimate a slow-moving trend, typically $q=1$ is a good choice for quarterly data (a 3-term moving average), a reasonable choice for the

weights is $B_j = 1/4q$ for $j = \pm q$, and $B_j = 1/2q$ otherwise. Implement a moving Average by convolving a time series with a vector of weights using CONV. You can not apply a symmetric moving Average to the q observations at the beginning and end of series. The results found in consciousness loss. One option is to use an asymmetric moving average at the end of the series to preserve all observations.

Selecting a correct threshold value: To find a correct and optimal value of the threshold we have to do various experiments on the database. In this work firstly we select a temporary value of threshold and calculate the recognition rate and error rate.

Assume that if image size is 112×92 and every pixel can have a maximum value of gray level is 255 hence we select a threshold as maximum pixels value for 112×92 size images.

Temporary threshold = maximum pixels value for 112×92

$$\begin{aligned} & \text{size images} \\ & = 112 \times 92 \times 255 \\ & = 2627520 \end{aligned}$$

Now we have a value of a threshold so feed this value for the matching process and calculate the recognition rate then again we select a comparatively minimal value randomly than previous value of threshold and again calculate the recognition rate and error rate then we compare the both result for different threshold values and we find that the minimum threshold value got a better result than higher threshold value. We use this method again and again to find the optimal value of threshold. In our paper we have got threshold value '15000'. Further reducing the value of a threshold it decreases the recognition rate, so the threshold value '15000' is set as a permanent threshold value of a proposed system for a dedicated AT&T face database. At a minimum threshold value we get a more accurate recognition rate and a minimum error rate. The various threshold value selection depends upon a dataset with their recognition rate and error rate are shown in Table 1.

Table 1: Comparison of various recognition rates and error rates depends upon the threshold value

Threshold=	2627520	200000	20000	15000
Recognition rate	56.00%	69.50%	89.50%	97.50%
Error rate	44.00%	30.50%	10.50%	2.50%

Matching process: In matching process we need a help of threshold value. In this paper we have already calculated the average matrix value for testing and training image, after that we also calculate the total difference value ' Δ ' and compare this total difference value to the threshold. Figure 4 also shows the matching process at which if the threshold value is less than or equal to the total difference matrix value otherwise face image will not be matched.

Total difference value = (Value of average matrix of testing image) – (Value of average matrix of training image)
 $\Delta = M_i - M_j$

Where

$M_i = i^{th}$ face image of testing dataset

$M_j = j^{th}$ face image of training dataset

Face image will be recognized or face image of testing will be matched with training image if and only if Threshold value $\leq \Delta$ (total difference value).

Proposed Algorithm: *Step 1.* Generate a new dataset and calculate a optimum threshold value. We got a threshold value = 15000.

Step 2. Read the image pixel by pixel:

$$A(i,j) = \sum_{i=0}^n \sum_{j=0}^m P(i,j) \quad \dots\dots\dots(2.4)$$

Where:

$A(i,j)$ = a sample of a facial image

$P(i,j)$ = 2D image representation

n = number of pixels in column of image
image

m = number of pixels in row of image

Step 3. Construct the Average Filtering window of size 3×3

$$Z(i,j) = \frac{1}{9} M(i,j)$$

$$Z(i,j) = \begin{matrix} \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix} \\ \frac{1}{9} \end{matrix}$$

Step 4. Construct the matrix from image by reading gray value of pixel from the range of 0 to 255. Figure 5 shows the matrix formation from a facial image.

Example :



22	112	20	35	90
99	200	220	25	80
24	25	60	50	70
22	8	9	55	75
240	211	130	150	80

Figure 5: Showing a matrix formation from a face image

Step 5. Apply the Average Filtering window on image constructed matrix.

Example:

Now calculate the average value of pixel having '200' gray value by adding all the eight neighbors' gray value and divide by the number of pixels in window which is 9.

So the value of central pixel of 3×3 window having '200' gray value is:

$$\begin{aligned} &= \frac{22+112+20+99+200+220+24+25+60}{9} \\ &= \frac{782}{9} \\ &= 86.88 \end{aligned}$$

Now we substitute value 86(integer value of 86.88) in place of the central pixel of window having value '200', and repeat this step for all the pixels present in image matrix.

$$\text{Image matrix} = \sum_{i=0}^n \sum_{j=0}^m P(i,j) \quad \dots\dots\dots(2.5)$$

$$\begin{aligned} \text{Average filter} &= Z(i,j) \\ &= \frac{1}{9} M(i,j) \quad \dots\dots\dots(2.6) \end{aligned}$$

Now after applying average filter on image-

$$\begin{aligned} \text{New matrix} &= \sum_{i=0}^n \sum_{j=0}^m P(i,j) * Z(i,j) \\ &= \frac{1}{9} \sum_{i=0}^n \sum_{j=0}^m P(i,j) * M(i,j) \quad \dots\dots\dots(2.7) \end{aligned}$$

Step 6. After calculating the matrix value for testing and training image dataset, we calculate a total difference value.

$$\begin{aligned} \text{Total difference value} &= (\text{Value of average matrix of testing} \\ &\quad \text{image}) - (\text{Value of average matrix of training image}) \\ &\Rightarrow \Delta = M_i - M_j \end{aligned}$$

Where

$M_i = i^{th}$ face image of testing dataset

$M_j = j^{th}$ face image of training dataset

Face image will be recognized or face image of testing will be matched with training image if and only if Threshold value $\leq \Delta$ (total difference value).

Step 7. Display the recognized face image.

EXPERIMENTAL RESULTS:

In this paper we used matrix based method. The distance between two features matrices can be directly computed. In the experiments we use Average Filtering method to calculate the feature matrices. There are a publicly available face database called AT&T face database is used to compare the proposed approach with the following algorithms: Eigenfaces, Fisherfaces, NPE, LFDA, CKFD, CNPE, SRDA, CLFDA and LS-CLFDA. In this experiment, subjects were asked to memorize intact and scrambled faces. Scrambled faces were chosen as a contrasting stimulus class because their parts are the same as the parts of a normal face, and yet we would not expect special, face-specific recognition abilities to be used in recognizing scrambled faces. After learning the normal and scrambled faces, subjects were given a forced-choice recognition task in which they identified facial features presented in isolation and in whole-face context. The whole-face test items were constructed such that the target and foil faces differed only with respect to the feature being tested. Examples of these two types of test for intact and scrambled faces are shown in Figure 5 and Figure 6. In the isolated part test condition, subjects would be asked to identify a face of person. In the full-face test condition, subjects would be asked to identify a person. If the recognition of normal faces involves representing their component parts to the same degree as the recognition of scrambled faces, then we should expect that identification of the features of normal faces will be just as good relative to the identification of the whole face as identification of the features of scrambled faces are relative to the identification of whole scrambled faces. However, if normal faces are recognized more holistically than scrambled faces, then there should be a disadvantage for identifying isolated features compared to whole faces for normal faces, relative to part and whole test performance for scrambled faces. To solve the challenge of dimensionality reduction and improve the accuracy of recognizing the faces of Local Fisher Discriminant Analysis; Hong Huang, Hailiang Feng, Chengyu Feng introduced Complete Local Fisher Discriminant Analysis with Laplacian Score ranking for face recognition [2] and this method gave a better results than other methods discussed previous and our proposed system give a better results on this method. The experiments are implemented on Intel Pentium-Quad Core N3510 Processor with 2GB RAM,500GB ROM and programmed in java language(version 1.7.0).

Experiments on the AT&T database

AT&T face database is a standard database for testing and evaluating state of the art face recognition algorithm. The proposed algorithm is tested on a subset of the AT&T face database this subset includes 400 images of 40 individuals (each individual has 10 images). It involves variations in facial expression, illumination and pose. In this database some people were with or without glasses, the heads are slightly rotated or tilted. The images in database are manually cropped and scaled to 112×92. There are some facial images of several persons from AT&T

database are shown in Figure 6 and 10 different pose images of a single person is shown in Figure 7.



Figure 6: Several original training samples from the AT&T face database



Figure 7: Ten images of one person in AT&T face database

Comparison of performance

In this work to minimize the recognition time we already constructed a new dataset from AT&T database, at which we calculate the all facial images without the noise and use this dataset to reduce the recognition time of our system. In the experiments, we used the first 3 images per class for training and the remaining images for testing. To further evaluate the performance we select first $l(l=2,4,6,8)$ images per class for training and remaining images for testing. Experimental results are shown in table 2, we can see that proposed Average Filtering Method for face recognition has the best result.

Comparison of performance based on the face recognition accuracy is calculated by the accurate recognized face images. Face recognition error rate is the ratio of numbers of the non-recognized face images of training and total number of the recognized face images of training set.

$$\text{Recognition error rate} = \frac{\text{Number of non-recognized faces}}{\text{Total number of faces in training}}$$

Example:

If non recognized faces in training set is 2 and total number of face images is 80 then the recognition accuracy will be as shown below-

$$\begin{aligned}\text{Recognition error rate} &= \frac{2}{80} \times 100\% \\ &= 2.5\%\end{aligned}$$

$$\begin{aligned}\text{Recognition accuracy} &= (100 - \text{error rate})\% \\ &= 97.50\%\end{aligned}$$

Table 2: comparison of different methods on the AT&T database for calculating recognition rate.

AT&T	l=2	l=4	l=6	l=8
Eigenfaces	72.81	86.79	93.00	95.37
Fisherfaces	81.04	92.49	95.78	97.75
NPE	81.67	92.63	95.56	96.38
LFDA	79.75	95.46	96.88	99.12
CKFD	75.69	92.52	96.19	98.00
CNPE	82.94	92.75	95.69	97.62
SRDA	83.34	92.39	96.25	98.00
CLFDA	84.83	96.65	98.88	99.38
LS-CLFDA	85.81	96.71	98.90	99.50
Proposed AFFR	97.50	98.34	100	100

Table 3: comparison of different methods on the AT&T database for calculating Error rate.

AT&T	l=2	l=4	l=6	l=8
Eigenfaces	27.19	13.21	7.00	4.63
Fisherfaces	18.96	7.51	4.22	2.25
NPE	18.33	7.37	4.44	3.70
LFDA	20.25	4.54	3.12	0.88
CKFD	24.69	7.48	3.81	2.00
CNPE	17.04	7.25	4.31	2.38
SRDA	16.66	7.61	3.75	2.00
CLFDA	15.17	3.35	1.12	0.62
LS-CLFDA	14.19	3.29	1.10	0.50
Proposed AFFR	2.50	1.66	00	00

Experimental Details

Experiments on AT&T database: we randomly select l ($l=2,4,6,8$) samples of each individual for training and the others for testing. We repeat the classification process 10 times by using different splits and calculate the average recognition rate Table 2 reports the best performance of different methods.

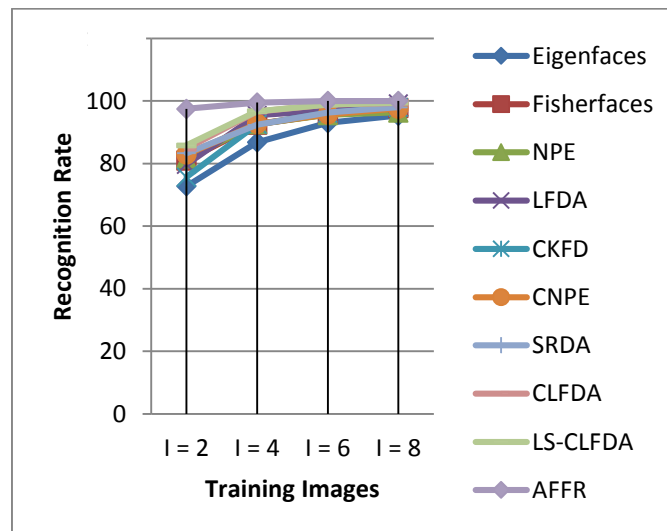


Figure 8: Average recognition rate of various methods on the AT&T database

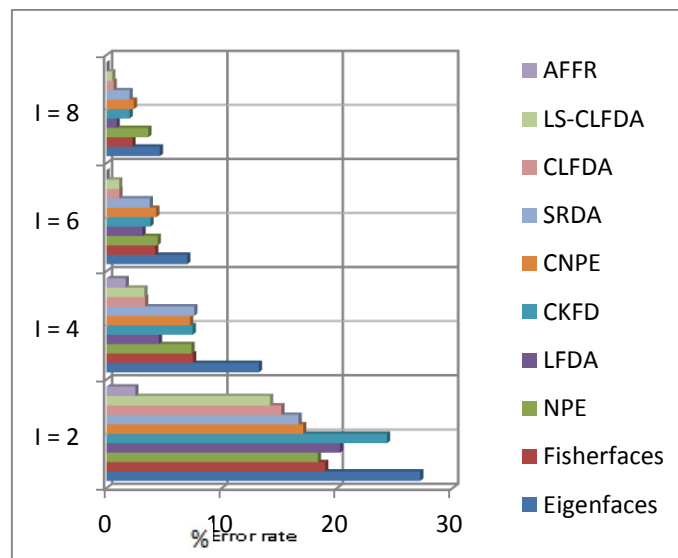


Figure 9: Recognition error rate with respect to training samples.

According to Table 2 or Figure 7 or Figure 8, we can obtain the following conclusions. In most cases, the complete methods perform better than the other methods and the reason may be that the Average Filtering method can take advantage of the regular and irregular discriminant information in the range and null image space. Our proposed method Average Filtering Face

Recognition (AFFR) is the top performer in all experimental cases, which indicates that other methods in extracting and representing image features for face recognition.

DISCUSSION

The experiment on AT&T database has been systematically performed. This experiment reveals a number of interesting points:

1. All approaches performed better in the optimal face subspace than in original image space.
2. In all experiments Average Filtering Face Recognition (AFFR) consistently performs better than other approaches on AT&T face database.
3. In our experiments Firstly we have to remove the noise and after removing noise Average Filter Face Recognition can identify the person with different expressions, poses and lighting conditions. So we perform face recognition using Average Filter which produces better results than other algorithms
4. In all our experiments, the number of training samples per subject is extensive than one. At times there might be only one training sample available for each subject. In such a case our AFFR method also gives better results.

CONCLUSION AND FUTURE WORK

As introduced in this paper, LFDA suffers from the small sample size problem, which creates local within-class scatter matrix singular. To overcome the intrinsic limitation of LFDA, a new method, called CLFDA, is proposed for face recognition .At first CLFDA removes the null space of local within-class scatter to extract the regular discriminant features in the null space of local between class scatter. Finally, both regular and irregular discriminant features are fused to Laplacian score for face recognition. Further, the CLFDA with Laplacian Score systems efficiency is reduced if the image is affected by Gaussian noise[6]. To overcome the problem of Gaussian noise we used Smooth mean filter as preprocessing phase in our proposed method and then we use Average Filtering Face Recognition method for recognizing the faces from the AT&T database. In future you can use a novel method to reduce the waiting time for recognition with better accuracy for recognizing the faces.

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