Face Recognition Using Various Illumination Normalization Techniques With Fuzzy K Nearest Neighbour Classifier

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ABSTRACT

The face recognition problem is made difficult by the great variability in head rotation and tilt, lighting intensity and angle, facial expression, aging, partial occlusion (e.g. Wearing Hats, scarves, glasses etc.), etc. In this paper I apply the various preprocessing techniques for illumination normalization for face images prior to face recognition accuracy testing. The aim is to find how these illumination normalization techniques reduces the computational complexity i.e. by either reducing the size of the image or by using the reduced feature set and how these techniques improves the face recognition rate. In this paper the illumination normalization techniques include: Log transformations, Power law transformations, Contrast stretching, Convolution filter, Histogram equalization and Homomorphic filter. Here K Means clustering algorithm is used to cluster the pixels in face image. Binary threshold is applied in the clusters. The proposed work is to compare the performance of various illumination normalization techniques with Homomorphic filters by computing the face recognition accuracy rate and find which illumination normalization technique produces good results with K means cluster using Fuzzy K nearest neighbour classifier. Face recognition accuracy is tested using the ORL face database.

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1. INTRODUCTION

Face recognition can be applied for a wide variety of problems like image and film processing, human-computer interaction, criminal identification etc. This has motivated researchers to develop computational models to identify the faces, which are relatively simple and easy to implement. A face image has high dimension.

A. Importance of Illumination Normalization

Illumination is considered one of the most difficult tasks for face recognition. Variations caused by pose, expression, occlusion or illumination is highly nonlinear, and making the detection task extremely complex. [1]. Here, the illumination normalization is addressed in particular. Illumination is a very important problem in face recognition. Research has shown that for a face image, the variability caused by illumination changes even exceeds the variability caused by identity changes [2]. As an example, Figure 1 shows the face images of the same subject under two different illuminations from Yale Face Database.

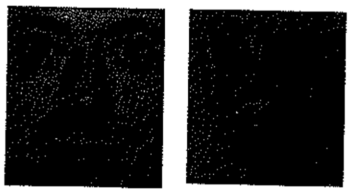

Figure 1: Examples of the same subject seen under different illuminations

Such illuminations will largely influence the performance of face recognition. I try to solve the illumination problem during the feature extraction stage, and keep the simplicity of the classifier. For this purpose preprocess the face image based on the following illumination normalization techniques [2] and find the face recognition accuracy rate and find which one is better. The techniques applied are

- Log transformations
- Power Law transformations
- Contrast stretching
- Convolution filter
- Histogram equalization
- Homomorphic filter

Well known contrast enhancement algorithms, such as histogram equalization, are global methods which do not consider important image details applied for face recognition. Logarithm transformations enhance low gray levels and compress the high ones. They are useful for non-uniform illumination distribution and shadowed images; however they are not effective for high bright images. Homomorphic filters enable dynamic range compression and contrast enhancement [3]. Homomorphic filters are sharpening filters using Fourier Transform and they are used for illumination normalization [4].

A. Algorithm for Face Recognition using Illumination Normalization Techniques

The face recognition of the proposed method has the following steps by first creating the training and test database using ORL face database :

Step 1: Preprocess the face images using any one of the illumination normalization techniques

Step2: Apply the K means cluster algorithm to group the pixels in the preprocessed image into given number of clusters.

Step 3: Create 2 clusters for the image obtained in step 2. Cluster 1 is assigned the gray level value 0 and cluster 2 is assigned the gray level value 255. The image now obtained is binary threshold K means clustered image.

Step 4: Repeat the step 1, 2, 3 for all images in the train database and the test database

Step 5: Use the Fuzzy K nearest neighbour classifier to classify the images in the test database to the closest class by comparing it with train database.

Step 6: Find the face recognition accuracy rate. i.e. the number of correct matches for the test in %.

Face recognition accuracy (in %) = (correct matches/Total number of tests) *100

2. Illumination Normalization Techniques

A. Log Transformations

The general form of the log transformation is

$$s = c \log (1 + r)$$

Where c is a constant, r is the input image, s is the output image and it is assumed that $r \geq 0$. The shape of the log curve is given in figure 2. It shows that this transformation maps a narrow range of low gray level values in the input image into a wider range of output values. The opposite is true of higher values of input levels. This log transformation could be used if we want to expand the valued of dark pixels in an image while compressing the higher-level values [4].

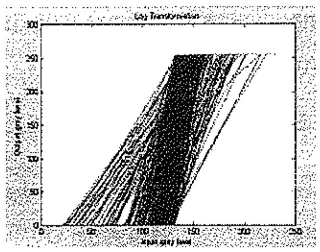

Figure 2 : Log transformation of face image in ORL face database

Any curve having the general shape of the log functions would accomplish this spreading / compressing of gray levels in an image. The log functions have an important characteristic that it compresses the dynamic range of images with large variations in pixel values.

B. Power Law Transformations

Power-law transformations have the basic form

$$s = cr^{\gamma}$$

Where c and γ are positive constants. As in the case of the log transformation, power-law curves with fractional values of γ map a narrow range of dark input values into a wider range of output values, with the opposite being true for higher values of input pixels. A family of possible transformations curves obtained simply by varying γ. Curves with values of $\gamma>1$ have exactly the opposite effect as those generated with values of $\gamma<1$.The transformation curve reduces to identity transformation when $c=\gamma=1$.The exponent in the power-law equation is referred to as gamma. Hence this transformation is also called as gamma transformation. Gamma transformation is useful for contrast enhancement [4].

C. Contrast Stretching

One of the simplest piecewise linear functions is a contrast-stretching transformation. Low contrast images can result from poor illumination. The idea behind contrast stretching is to increase the dynamic range of the gray levels in the image being processed. The contrast enhanced image is given by the following equation

$$g = \frac{1}{1+\left(\frac{m}{f}\right)^{r}}$$

Where g is the contrast enhanced image, m is the mean of the input image; f is the input image r is the constant [4].

D. Convolution Filter

The convolution filter is a linear spatial filter which has m × n mask. The process consists simply of moving the filter mask from point to point in an image. At each point (x, y), the response of the filter at that point is calculated using a predefined relationship. For linear spatial relationship, the response is given by a sum of products of the filter coefficients and the corresponding image pixels in the area spanned by the filter mask. The mask m × n can be 3 × 3 filter. The 3 × 3 filter used here for illumination normalization is [0 -2 0; -2 10 -2; 0 -2 0] [2].

E. Histogram Equalization

It is enhancing contrast using histogram equalization. It enhances the contrast of images by transforming the values in an intensity image, or the values in the colormap of an indexed image, so that the histogram of the output image approximately matches a specified histogram. The images obtained as output has histogram equalized [4].

F. Homomorphic filters

The Homomorphic filters are based on the well-known illumination-reflectance model. This model is designed to develop a frequency domain procedure for improving the appearance of an image by simultaneous gray-level range compression and contrast enhancement. An image f(x, y) can be expressed as the product of the illumination i(x, y), and the reflectance component r(x, y) as follows:

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

This equation cannot be used to operate separately on the frequency components of illumination and reflectance directly because the Fourier transform of the product of the two functions is not separable. So, equation (1) can't be expressed as :

$$\Im\{f(x,y)\} = \Im\{i(x,y)\}.\Im\{r(x,y)\} \qquad (2)$$

But if image f(x, y) can be defined as follows-

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

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

Then

$$\Im\{z(x,y)\} = \Im\{\ln f(x,y)\}$$
$$= \Im\{\ln i(x,y)\} + \Im\{\ln r(x,y)\}$$

Or

$$Z(u,v) = F_i(u,v) + F_r(u,v) \qquad (3)$$

Where, $F_i(u,v)$ and $F_r(u,v)$ in equation (3) are the Fourier transforms of the terms defined.[4] The function Z(u,v) can be processed by means of a filter function H(u,v) and can be expressed as-

$$S(u,v) = H(u,v).Z(u,v)$$
$$= H(u,v).F_i(u,v) + H(u,v).F_r(u,v) \qquad (4)$$

Where S (u, v) is the Fourier transform of the result. In the spatial domain-

$$s(x,y) = \Im^{-1}\{S(u,v)\}$$
$$= \Im^{-1}\{H(u,v).F_i(u,v)\} + \Im^{-1}\{H(u,v).F_r(u,v)\}$$

By letting

$$i'(x,y) = \Im^{-1}\{H(u,v).F_i(u,v)\}$$

and

$$r'(x,y) = \Im^{-1}\{H(u,v).F_r(u,v)\} \qquad (5)$$

Finally the equation becomes

$$s(x,y) = i'(x,y) + r'(x,y)$$
$$g(x,y) = e^{s(x,y)}$$
$$g(x,y) = e^{i'(x,y)}.e^{r'(x,y)}$$
$$g(x,y) = i_0(x,y).r_0(x,y) \qquad (6)$$

where

$i_0(x,y) = e^{i'(x,y)}$ and $r_0(x,y) = e^{r'(x,y)}$

are the illumination and the reflectance components of the output images. But as z(x, y) was formed by taking the logarithm of the original image f(x, y) , the inverse (exponential) operation yields desired enhanced form of the original image, denoted by the g(x, y). So, the procedure is taking logarithm and exponential sequentially yield the suitable version of the original image. This method is based on a special case of a class of systems known as Homomorphic system. The filter transfer function H (u, v) is known as the Homomorphic filter function which acts on the illumination and the reflectance components of the input image separately. The Illumination component of an image is generally characterized by the slow spatial variations while the reflectance components vary abruptly, particularly at the junctions of the dissimilar objects. These characteristics actually lead to associate the low frequencies of the Fourier transform of the logarithm of an image with illumination and the high frequencies with reflectance. [5]

3. Implementation

A. Experimental Work

The experimental work is done using the Olivetti and Oracle Research Laboratory (ORL) Face Database. ORL face database is used in order to test our method in the presence of head pose variations. There are 10 different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying lighting, facial expressions (open / closed eyes, smiling / not smiling), facial details (glasses / no glasses) and head pose (tilting and rotation up to 20 degrees). All the images were taken against a dark homogeneous background.

ORL database of 400 images of different subjects of size 92 X 112 is taken for experimentation. The 400 images of 40 subjects in 10 different poses, expressions, illumination etc are stored as such in test database. In order to do experimentation with illumination normalization a train database and a test database is created.

Out of the 400 images 200 images (i.e. first 5 images of 40 subjects with 5 different poses) are chosen as train database. Remaining 200 images (i.e. second 5 images of 40 subjects with 5 different poses) are chosen as test database without overlapping. 400 images of 40 subjects are taken as another test database with overlapping in train database. Here the 50% of images in the test database is in train database.

Figure 3: Sample Face Images In ORL Face Database

Figure 4 shows the whole set of 40 individuals, 10 images per person from the ORL database.

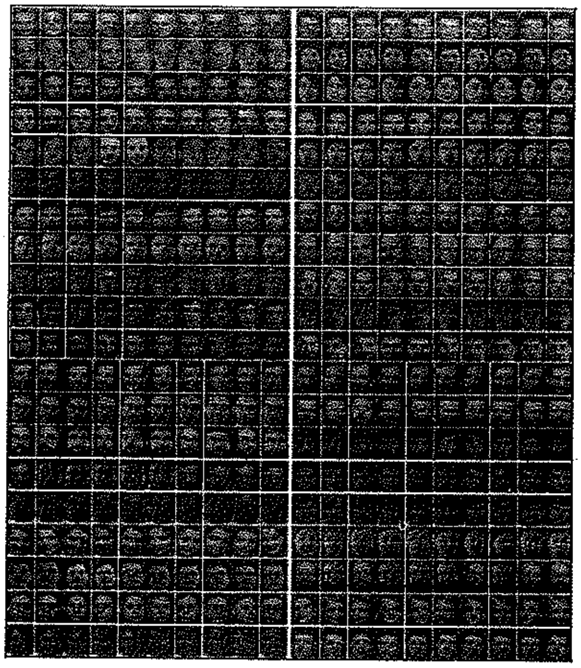

Figure 4 : ORL Face Database Of 400 Face Images

A. Implementing Illumination Normalization Techniques

1) Log Transformations

The general form of the log transformation is $s = c \log (1 + r)$. r is the input image. s is the enhanced image. c is a constant which is equal to 1.2. In Figure 5 first row shows the sample images in train database and the second row shows the log transformation of the images. This shows that the images are enhanced and the effect of illumination is normalized.

Figure 5 : A) Original Images B) Log Transformation Applied Image

2) Power Law Transformations

Power-law transformations have the basic form

$$s = cr^{\gamma}$$

where c and γ are positive constants. Here $\gamma = 0.3$. Figure 6 shows the power law transformation of the images

Figure 6 : Power Law Transformation Applied Image

3) Contrast stretching

The contrast enhanced image is given by the following equation

$$g = \frac{1}{1 + \left(\frac{m}{f}\right)} r$$

Where g is the contrast enhanced image, m is the mean of the input image; f is the input image γ is the constant. Here $\gamma = 7$. Figure 7 shows contrast stretched images.

Figure 7 : Contrast Stretched Images

4) Convolution filter

The 3×3 filter used here for illumination normalization is [0 -2 0; -2 10 -2; 0 -2 0]. Figure 8 shows the convolution filter applied images.

Figure 8 : Convolution Filter Applied Image

5) Histogram Equalization

It enhances the contrast of images by transforming the values in an intensity image, or the values in the colormap of an indexed image, so that the histogram of the output image approximately matches a specified histogram. The images obtained as output has histogram equalized. Figure 9 shows the histogram equalized images.

Figure 9 : Histogram Equalized Image

6) Homomorphic filer

Create a homomorphic filter H and find the Fourier transform of the original image F. Multiply H with F and find the inverse Fourier transform of the multiplied image. Take the exponent part of the multiplied image to obtain homomorphic filtered image. Figure 10 shows the homomorphic filtered image and figure 11 shows the histogram of homomorphic filtered image. The histogram of homomorphic filtered image shows that pixels are concentrated at two ends dark and bright pixels.

Figure 10 : A Homomorphic Filtered Image

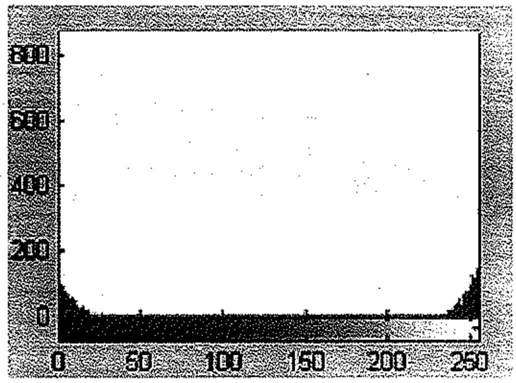

Figure 11 : Histogram Of Homomorphic Filtered Image

4. K MEANS CLUSTERING ALGORITHM

A. Introduction

The K-Means clustering algorithm produces K clusters in the image, by simply assigning each point to the cluster whose centroid is closest to it. Centroids are recomputed as soon as a new point is added to the cluster. Initially, K randomly chosen points are designated as the seed points, or initial clusters. The main benefit of K-Means clustering is that it runs in linear time unlike agglomerative clustering algorithms which run in quadratic or cubic time, depending on the linkage used.

The k-means algorithm is hard partitioning methods and this is simple and popular, though the results are not always reliable. The k-means algorithm allocates each data point to one of c clusters to minimize the within-cluster sum of squares:

$$\sum_{i=1}^{c} \sum_{k \in A_i} \left\| x_k - v_i \right\|^2$$

Where A_i is a set of objects (data points) in the i-th cluster and v_i is the mean for that points over cluster i. In k-means clustering the cluster prototype is a point [8].

In this paper 2 clusters are created for the given image. Cluster 1 is assigned the gray level value 0 and cluster 2 is assigned the gray level value 255.The resultant image obtained is binary threshold K means Homomorphic filtered image. Figure 12 shows the sample of binary image of ORL face database and its histogram. Histogram shows that the pixel values are either 0 or 255.

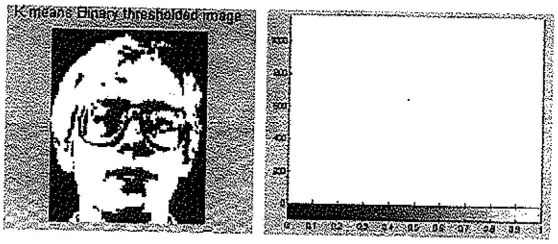

Figure 12 : A) Binary Threshold Image
B) Histogram Of Binary Threshold Image

5. Fuzzy K nearest neighbour classifier

In this paper, fuzzy membership degree and each class center are gained through FKNN [7] algorithm. With FKNN algorithm, the computations of the membership degree can be realized through a sequence of steps:

Step 1 : Compute the Euclidean distance matrix between pairs of feature vectors in training set.

Step 2 : Set diagonal elements of this Euclidean distance matrix to infinity.

Step 3 : Sort the distance matrix (treat each of its columns separately) in an ascending order. Collect the corresponding class labels of the patterns located in the closest neighborhood of the pattern under consideration (as we are concerned with '' neighbors, this returns a list of '' integers).

Step4: Compute the membership degree to class 'i' for j^{th} pattern using the expression proposed in the literature [7]

$$u_{ij} = \begin{cases} 0.51 + 0.49 \times (n_{ij}/k) \\ 0.49 \times (n_{ij}/k) \end{cases} \tag{8}$$

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

$$\sum_{i=1}^{c} u_{ij} = 1$$

$$0 < \sum_{j=1}^{N} u_{ij} < N \tag{9}$$

Taking into account the fuzzy membership degree, the mean vector of each class is

$$\hat{m}_i = \frac{\sum_{j=1}^{N} u_{ij}^{\rho} x_j}{\sum_{j=1}^{M} u_{ij}^{\rho}} \tag{10}$$

Where ρ is a constant which controls the influence of fuzzy membership degree.

Therefore, the class center matrix m and the fuzzy membership matrix U can be achieved with the result of FKNN.

$$U = \lfloor u_{ij} \rfloor, i = 1,2\Lambda\ c, j = 1,2\Lambda\ N \tag{11}$$

$$m = \lfloor \hat{m}_i \rfloor, i = 1,2\Lambda\ c \tag{12}$$

6. Results

Face recognition is tested by using the various illumination normalization techniques with K means clustering algorithm with FKNN Classifier. The results are compared

A. Analysis

Face recognition is tested by using the test database with 200 images and the train database with 200 images without any overlapping of images in the test and train databases. It was found that the face recognition rate using this convolution filter with K means clustering algorithm with FKNN Classifier is 89%. Table I shows the result.

Table 1: Face Recognition Accuracy in % Using the Various Illumination Normalization Techniques

Total No. of test Images	Face Recognition using Various Illumination Normalization techniques with K means plus FKNN Classifier			
	Log	*Power Law*	*Contrast Stretching*	*Convolution filter*
200	138 correct matches	152 correct matches	171 correct matches	178 correct matches
Recognition Accuracy %	69%	76%	85.5%	89%

It was found that face recognition accuracy using histogram equalization with K means clustering algorithm with FKNN Classifier is 76%

Table 2 : Face Recognition Accuracy in % Using Histogram Equalization

Total No. of test Images	Face Recognition using Histogram Equalization
200	152 correct matches
Recognition Accuracy %	76%

Table 3 : Face Recognition Accuracy In % Using The Homomorphism Filter

Total No. of test Images	Face Recognition using Homomorphic filter with K means plus FKNN Classifier
200	173 correct matches
Recognition Accuracy %	86.5%

The size of the image obtained with binary threshold K means clustered homomorphic filtered can be reduced by half by either removing the even or odd rows or columns from the processed image even without much loss in information stored. Figure 13 a shows the original image obtained by binary threshold K means homomorphic filtered image and figure 13 b shows the image reduced by 2 from 92 X 112 to 46 X 112 by removing the even rows in the image and 13c shows image reduced by 2 from 92 X 112 to 92 X 56 and figure 13 d shows the image reduced by 4 of the original image by removing the even rows and even columns from the original image with size 46 X 56. It shows that the information lost is less in case of rows and columns reduction and this reduced feature set can be used for face recognition.

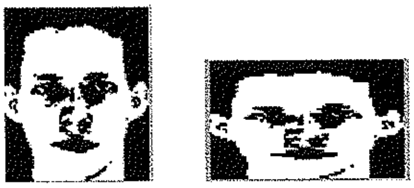

Figure 12 : A) Image Size 92 X 112 B) Image Size Reduced By2rows Reduction 46 X 112

Figure 12 C) Image With Cols Reduction 92 X 56 D) Image Reduced By 4 Rows & Coumns Reduction 46 X 56

It was found that face recognition accuracy by reduction of even rows or columns or both even rows and columns using the proposed method with FKNN classifier is same as that of the processed image with original size. It is given in Table 4. Reducing the image size by 4 results in less accuracy. Table V shows the reduction of image size by 3. Figure 13 shows the image obtained by removing every third rows or columns or both

Figure 14 a) **Figure 14 b)** **Figure 14 c)**

Figure 14a) Image obtained by removing every third rows 31 X 112 14 b) Image obtained by removing every third columns 92 X 38 14 c) Image obtained by removing every third rows and columns 31 X 38

Table 4 : Face Recognition Accuracy in % By Reduction in Image Size By 2 or 4

Total No. of test Images	Face Recognition using proposed method With FKNN Where K=3,5,10		
	Removing even rows	*Removing even columns*	*Removing even rows and columns*
200	172 correct matches	173 correct matches	128 correct matches
Recognition Accuracy %	86 %	86.5%	64%

Table 5 : Face Recognition Accuracy In % By Reduction In Image Size By 3 or 6

Total No. of test Images	Face Recognition using proposed method With FKNN Where K=3 5 10		
	Removing every third rows	*Removing every third columns*	*Removing every third rows and columns*
200	172 correct matches	171 correct matches	130 correct matches
Recognition Accuracy %	86 %	85.5%	65%

6. Conclusion

Face recognition is a popular biometric authentication since it does not require the aid of the tester like other biometric methods iris, finger print etc. A face image has high dimension. The number of gray levels used in this paper is only 2 and it reduces the computational complexity and Fuzzy K Nearest neighbour classifier with K means clustering algorithm produces good results than nearest neighbour classifier. Among the illumination normalization techniques convolution filter produces highest accuracy rate of 89% with ORL face database. Using 2 gray level values 0 and 255 only the method has achieved the face recognition accuracy of 86.5% even by removing the even columns with homomorphic filter applied image. The size of the image obtained with binary threshold K means clustered homomorphic filtered can be reduced by half without much loss in information stored. The reduction in the processed image is possible since only 0's and 255's are repeated in the image.

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