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# PERFORMANCE EVALUATION OF ILLUMINATION NORMALIZATION TECHNIQUES FOR FACE RECOGNITION

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## ABSTRACT

Changes in lighting condition impact the appearance of face images to a large extent. Therefore it becomes very difficult to recognize a face under different lighting conditions. The face images have to be normalized to overcome the illumination variation to get recognized. The work presented here analyzes the performance of the illumination normalization methods of face images like DCT (Discrete Cosine Transform) normalization, Wavelet Denoising, Gradient Faces, Local Contrast Enhancement, and Weber's law under different lighting conditions. The face images are preprocessed and normalized by each normalizing method to reduce the effect of illumination. To analyze the performance of each method, the features of these preprocessed images are extracted using Principal Component Analysis (PCA) and the recognition is done based on Euclidean Distance. In this paper, the advantages and drawbacks of each method are analyzed. The recognition rate and computational time of these methods are compared. The Extended Yale B database is used in this work.

**KEYWORDS:** Discrete Cosine Transform, Gradient Domain, Local Contrast Enhancement, Principal Component Analysis, Wavelet Denoising, Weber's Law

## INTRODUCTION

Automatic face recognition has a wide scope in applications like authentication, security, mug shot data base matching and surveillance. The lighting condition changes from day to night and also between indoor and outdoor environments. These variations severely affect the appearance of the face [1]-[2]. The potential change caused by intra personal variation (variation within the same class) is much larger compared to that of inter-personal variations (variation between classes) [1]. The 3 D face structure when observed under direct lighting source could produce a shadow that would highlight or deter some facial features. As a result the face recognition tends to fail if the test image has a different lighting condition than that of the training images. The methods to solve the illumination problem can be generally classified into three categories as discussed below. [12].

### Face Image Enhancement

This method eliminates the intensity variations caused by the various lighting conditions. It uses preprocessing techniques to normalize the images under different illumination conditions. For instance, global and local contrast enhancement techniques like histogram equalization, region-based histogram equalization, block-based histogram equalization, and logarithmic transforms have been widely used for illumination normalization [3]-[7].

### Invariant Feature Extraction

This method considers stable facial features that are not affected by the lighting changes. For example, Edge maps, Local binary pattern, Linear Discriminant Analysis (LDA) considers features which are not sensitive to illumination variations. Statistical methods for feature extraction largely rely on the representativeness of the training samples [8].

**Face Modeling**

The illumination at different angles causes shadow in the face image due to the 3-D structure of human face. Face images with fixed pose under varying illumination from different directions form a convex cone called illumination cone. It is represented by a low-dimensional linear subspace whose basis vectors are estimated from training images. It requires many training images under different illumination conditions [9]-[10].

In this work, face image enhancement has been chosen to solve the effect of illumination because it is simple to implement and it does not require a model to represent the training images. The rest of the paper is organized as follows: In section 2, the detailed theoretical background of the illumination normalization methods are given. In section 3, the methodology of illumination normalization and the different stages of the experiment are described. In section 4, the experimental results are presented and their performance is compared. Conclusion is given in section 5.

## ILLUMINATION NORMALIZATION METHODS

The face image I(x, y) is considered as the product of the reflectance component R(x, y) and the illumination component L(x, y) [11].

$$I(x,y) = R(x,y)L(x,y) \tag{1}$$

It is difficult to separate the reflectance and the luminance components from face images. Therefore, it is assumed that luminance L varies slowly (low frequency component) and reflectance R varies abruptly (high frequency component) between the adjacent pixels in order to solve the problem.

**DCT Normalization**

Discrete Cosine Transform converts the image from spatial domain to frequency domain. DCT is performed on the facial image to obtain all frequency components of the image. Illumination components of the image can be removed by setting low frequency components to zero [12].

Taking logarithm transform on (1), we have

$$\log I(x,y) = \log R(x,y) + \log L(x,y) \tag{2}$$

From (2), if the incident illumination is L(x, y) and the desired uniform illumination is l'(l' is identical for every pixel of an image), we have

$$\begin{aligned} \log I'(x,y) &= \log R(x,y) + \log l' \\ &= \log R(x,y) + \log L(x,y) - \varepsilon(x,y) \\ &= \log I(x,y) - \varepsilon(x,y) \end{aligned} \tag{3}$$

where $\varepsilon(x,y) = \log L(x,y) - \log l'$

I'(x, y) is pixel value under desired illumination. From (3), the normalized face image is obtained by subtracting the compensation term ε (x, y) from the original image. The compensation term ε (x, y) is the difference between the normalized illumination and the estimated original illumination in the logarithm domain. To remove the low frequency components, the product of DCT basis image and corresponding coefficient are subtracted from the original image. To set 'n' DCT coefficients to zero,

$$I'(x,y) = \sum_{u=0}^{M-1}\sum_{v=0}^{N-1} E(u,v) - \sum_{i=1}^{n} E(u_i, v_i)$$

$$= I(x,y) - \sum_{i=1}^{n} E(u_i, v_i)$$

Where

$$E(u,v) = \alpha(u)\alpha(v)C(u,v)\cos\left[\frac{\Pi(2x+1)u}{2M}\right]\cos\left[\frac{\Pi(2y+1)v}{2N}\right]$$

$$C(u,v) = \alpha(u)\alpha(v)\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} I(x,y)\cos\left[\frac{\Pi(2x+1)u}{2M}\right] * \cos\left[\frac{\Pi(2y+1)v}{2N}\right]$$

I'(x, y) is the desired normalized face image in the logarithm domain. Therefore, discarding low-frequency DCT coefficients in the logarithm domain is equivalent to compensating for illumination variations.

The first DCT coefficient (i.e., the DC component) determines the overall illumination of a face image.

$$C(0,0) = \log\mu.\sqrt{MN}$$

where C (0, 0) is the DC coefficient of the logarithm image. $\mu$ is the average gray level intensity of the face image. Since low frequency features are discarded, unstable facial feature hair is not considered and it reduces computational complexity. The main issue of this method is the choice of number of DCT coefficients to be considered. Illumination variations and facial features are not perfectly separated with respect to the frequency components; therefore some facial features will be sacrificed.

**Wavelet Denoising**

Wavelet transform decomposes the image into different frequency sub bands at multi-scale. This method extracts illumination invariant component R from (1) by performing logarithm operator on the image.

$$I' = R' + L' \tag{4}$$

where I' ≈ log (I), R' ≈ log(R), and L' ≈ log (L).

Given face images of a person under different lighting conditions, the frequency corresponding to *R* (key facial features) is different. To eliminate the illumination variation, an estimate for key facial features *R* with small mean-square error is given by

$$\min R'^2 = \min(I' - L')^2 \tag{5}$$

R' is obtained by solving optimization problem (5) such that key facial features are robust to different lighting. The facial features *R* are equivalent to "noise" in denoising model, therefore key facial features *R is* extracted from multi-scale space. Low frequency wavelet coefficients which are highly sensitive to illumination variation have been discarded. Instead of directly estimating *R'* by (5), *L'* is estimated by wavelet denoising model, and then *R'* is estimate d by (4) [13].

The image is decomposed into four sub bands and sub sampled using 2D discrete wavelet transform. The wavelet coefficients of the signal L' denoted by X, is obtained from the wavelet coefficients of the logarithm image data I' by suppressing the signal R' with a nonlinear thresholding function thresh [14] .

$$thresh(x) = \begin{cases} X - T & \text{if } X \geq T \\ X + T & \text{if } X \leq -T \\ 0 & \text{if } |X| < T \end{cases}$$

The threshold *T* can be calculated as follows

$$T = \frac{\sigma^2}{\sigma_x}$$

$$\sigma = \frac{median\ |Y_{ij}|}{\lambda} \qquad Y_{ij} \in subband\ HH_1$$

$$\sigma_{x} = \sqrt{\max\left(\sigma_Y^2 - \sigma^2, 0\right)}$$

$$\frac{1}{n^2}\sum_{i,j=1}^{n} Y_{ij}^{\ 2}$$

In general, the range of λ is from 0.01 to 0.30(λ=0.1 for implementation).

Wavelet transform has the advantage of multi-scale analysis, better edge-preserving ability in low frequency illumination fields, fast computation and simpler parameter selection. The main drawback is that the recognition rate depends on the selection of λ.

**Gradient Faces**

This method converts the image from pixel domain to gradient domain. Gradient domain considers the relationship between the neighboring pixel and it reveals underlying inherent structure of the image. [15]

Image gradients extract illumination insensitive features like edge from the facial image. Given an image I(x, y) the ratio of y gradient $I(x, y)\ \partial I(x, y)/\partial y$ to x gradient $I(x, y)\ \partial I(x, y)/\partial x$ is computed as follows.

From (1)

$$\mathbf{I}(x - i\Delta x, y - j\Delta y) = R(x - i\Delta x, y - j\Delta y)\ L(x - i\Delta x, y - j\Delta y) \qquad (6)$$

Subtracting (1) from (6)

$$I(x - i\Delta x, y - j\Delta y) - I(x, y) = R(x - i\Delta x, y - j\Delta y)L(x - i\Delta x, y - j\Delta y) - R(x, y)L(x, y)$$

Based on the assumption, L is approximately smooth

$$I(x - i\Delta x, y - j\Delta y) - I(x, y) \approx R(x - i\Delta x, y - j\Delta y)L(x, y) - R(x, y)L(x, y)$$

$$\approx \big(R(x - i\Delta x, y - j\Delta y) - R(x, y)\big)L(x, y) \qquad (7)$$

Taking the X gradient of (7)

$$\frac{\partial I(x,y)}{\partial x} \approx L(x, y)\frac{\partial R(x,y)}{\partial x} \qquad (8)$$

Similarly we have

$$\frac{\partial I(x,y)}{\partial y} \approx L(x, y)\frac{\partial R(x,y)}{\partial y} \qquad (9)$$

Dividing (9) by (8),

$$\frac{\frac{\partial I(x,y)}{\partial y}}{\frac{\partial I(x,y)}{\partial x}} = \frac{\frac{\partial R(x,y)}{\partial y}}{\frac{\partial R(x,y)}{\partial x}}$$

The ratio of y-gradient to x gradient will be infinity when x-gradient is zero. Thus the ratio cannot be directly used as illumination insensitive measure. Gradient face (GF) of an image I(x, y) is defined as

$$GF(x,y) = arctan\left(\frac{\frac{\partial I(x,y)}{\partial y}}{\frac{\partial I(x,y)}{\partial x}}\right)$$

Before computing the gradient, the image is smoothened by convolving with the Gaussian kernel function so that it reduces the noise and shadows and makes gradients more stable. But, first order derivatives are little sensitive to lumination.

**Local Contrast Enhancement (LCE)**

LCE increases the visual contrast of the image in a designated intensity range. The contrast of a gray scale image is enhanced by representing the image data as the local contrast for each pixel in logarithm domain. LCE is mainly useful for improving the contrast of the image [16]. The local contrast δ (x, y) for a pixel (x, y) with luminance value I(x, y)

$$\delta(x,y) = \begin{cases} I(x,y)/\overline{I(x,y)} & , if\ I(x,y) > \theta\ and\ \overline{(I(x,y))} > \theta \\ 0 & \text{otherwise} \end{cases}$$

where θ is a predefined threshold (θ=1 for implementation). I(x, y) denotes the average luminance value of the neighborhoods of the pixel (x, y), and the neighborhood window size of a pixel adopted in the current implementation is 5x5 pixels as

$$\overline{I(x,y)} = \frac{1}{25}\sum_{i=-2}^{2}\sum_{j=-2}^{2} I(x+i, y+j)$$

Instead of using the original intensity value of the pixel, local contrast value is used. Local contrast is defined as the ratio of the original intensity of the pixel to the average of its surrounding pixels, in logarithm domain. The local contrast value measured may be positive or negative. Therefore the data has to be normalized. The local contrast value for a pixel (m, n) is normalized by

$f(x, y) = \varphi \times (\delta(x, y) - \delta_{min}) / (\delta_{max} - \delta_{min})$

where f(x,y) denotes the normalized local contrast value of a pixel (x, y), φ denotes the maximum gray level in the image data range and δ max and δ min represent the maximum and minimum local contrast values of all pixels., LCE can be used when there are significant variations among the images, and even within the single image. The disadvantage is that the recognition rate depends on the choice of window size.

**Weber Faces**

Ernst Weber in 1983 proposed that the ratio between the smallest percentage change in the stimulus (ΔImin) and the background level is a constant

$$\frac{\Delta Imin}{I} = K$$

Where K is the Weber fraction which remains constant despite of the variation in the I term. Given the face image, for each pixel, two terms are computed: relative intensity difference of the current pixel against its neighbor, intensity of the current pixel. The obtained ratio image is called Weber Face [17].

The ratio image is computed by Weber local description (WLD) proposed by Chen-et al [18] consists of two components differential excitation and orientation. By applying WLD to the face image Weber Face is obtained.

$$WF(x,y) = arctan(\alpha \sum_{i \in A} \sum_{j \in A} \frac{I(x,y) - I(x-i\Delta x, y-i\Delta y)}{I(x,y)}) \quad (10)$$

where A= {-1, 0, 1}

The arc tangent prevents the output magnitude being large and partially suppresses the side effect of noise. $I_c$ is the intensity of the current pixel. $I_i$ denotes the intensities of neighbors (i=0, 1,…….,P-1) (P=8 here).α is the adjusting parameter for the intensity difference between the neighboring pixels(α=2 used for implementation.

From (1) we have

$$I(x - i\Delta x, y - j\Delta y) = R(x - i\Delta x, y - j\Delta y)\, L(x - i\Delta x, y - j\Delta y) \quad (11)$$

Since illumination component varies slowly except shadow boundaries

$$L(x - i\Delta x, y - j\Delta y) \approx L(x,y) \quad (12)$$

By substituting (1),(10),(11) into (10)

$$WF(x,y) = \mathrm{arctan}\,(\alpha \sum_{i \in A} \sum_{j \in A} \frac{R(x,y) - R(x-i\Delta x, y-i\Delta y)}{R(x,y)})$$

Here the Laplace operator is used to measure local intensity variation and edge detection. It is sensitive to noise; the image is smoothened using Gaussian filter. Thus it reduces the side effect of shadow boundaries. Weber face preserves the most important facial features. Weber's law breaks down for very bright and very dark luminance level.

## METHODOLOGY

### Illumination Normalization

Illumination normalization methods preserve the facial features and minimize the undesired artifacts. In this work, extended Yale B face database is used. This database consists of 2,470 front-face images of 38 individuals with 65 illumination conditions [10]. The experiments were performed using 30 subjects with 16 sample images for each subject under the illumination condition of 0-70$^{\circ}$.

These images are normalized using the techniques namely DCT normalization, Wavelet Denoising, Gradient Faces, Local Contrast Enhancement and Weber Faces. Figure 1 shows the images after illumination normalization by different methods.

**Figure 1a: Images under Different Illumination from Extended Yale B Database**

**Figure 1b: Results of DCT Normalization**

**Figure 1c: Results of Wavelet Denoising**

**Figure 1d: Gradient Faces**

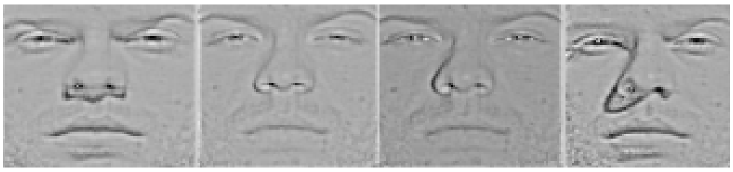

**Figure 1e: Results of Local Contrast Enhancement**

**Figure 1f: Weber Faces**

## Recognition

The different stages of illumination invariant face recognition system are shown in Figure 2.

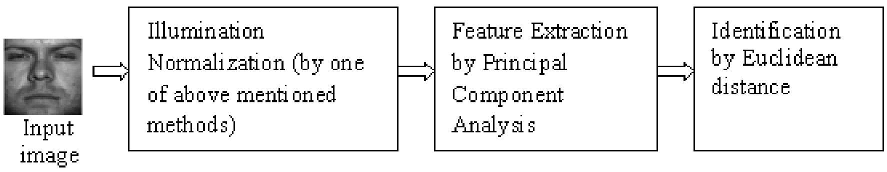


**Figure 2: Block Diagram of Illumination Invariant Face Recognition System**

The performance of these illumination normalization methods are tested by evaluating the recognition rate in a face recognition system.

First the face images are cropped to the size 192 x 168. The images are then normalized using one of above techniques with MATLAB 7.10 in a Pentium dual core PC system running at 2GHz. Of the 16 normalized images per subject, 8 images are selected for training and the remaining 8 images for testing. DCT normalization transforms the image to frequency domain. And Wavelet denoising converts the pixel values to wavelet coefficients. Gradient method converts the image from pixel domain to gradient domain. LCE retains the image in pixel domain. Weber's law transforms the pixel values to second derivative and reduces the illumination sensitive components.

The face image is considered as a very high dimensional space and each pixel value corresponds to its component. The dimension can be reduced by selecting the principal components of the face image. These principal components inherently represent the face images in lower dimension. The recognition of the test image is based on selecting the class to which it has the minimum Euclidean distance. Similarly the recognition rate is found with images that have been normalized with the other illumination normalization techniques. The recognition rate obtained for the different illumination normalization methods is shown in Table 1.

**Table 1: Comparison of Recognition Performance with 5 Different Methods**

| Methods | No. of Test Images | No. of Recognized Images | Recognition Rate (%) |
|---|---|---|---|
| DCT | 240 | 140 | 70.8 |
| Wavelet | 240 | 138 | 57.5 |
| Gradient face | 240 | 222 | 92.5 |
| LCE | 240 | 94 | 39.2 |
| Weber faces | 240 | 236 | 98.3 |

## RESULTS AND DISCUSSIONS

Figure 3 shows the performance comparison of illumination normalization techniques. From the results, it is evident that illumination normalization using Weber's law gives better recognition rate when compared to other techniques.

Figure 1a shows the sample of training images of class 1 under different illumination conditions from extended Yale database. Figure 1b shows the DCT normalized facial images. The recognition rate is lower because while discarding low frequency coefficients some facial features are also eliminated. It is difficult to decide the appropriate number of DCT coefficients to be considered.

When the lighting direction changes shadows are produced in the facial image. The shadows and the facial feature in the shadow region lie in the same frequency band. Therefore when the illumination component is discarded, the facial features are also lost. Elimination of these low frequency coefficients reduces the computational complexity but reduces the recognition rate.

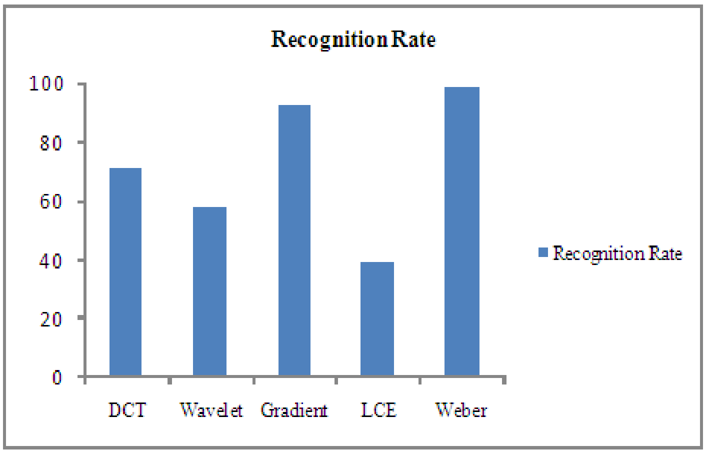


**Figure 3: Recognition Rate Vs Illumination Normalization Methods**

Figure 1c shows the images after wavelet denoising. This method is fast since it analyzes the image in multi-scale and it eliminates the low frequency coefficients. The recognition rate depends on the parameter λ. It is difficult to select the appropriate value for λ since it depends on the illumination condition.

Figure 1d shows the gradient faces. Taking gradient in the face image provides edge strength and it points in the direction of greatest rate of change of intensity. Gradient faces gives a good performance, but first derivatives are little sensitive to illumination. Change in lighting direction changes the magnitude of gradient greatly.

Figure 1e shows the image after local contrast enhancement. LCE avoids the changes caused in the face image due to illumination. Even though LCE produces features which are less sensitive to illumination, it also produces undesired halos. Further, LCE cannot distinguish the images of different persons since the image is considered in pixel domain.

Weber faces shown in Figure 1f gives a better recognition rate when compared with other methods because Weber local descriptor is robust and it can handle the illumination changes. These normalization methods reduce the effect of illumination, but minimize the interclass distance. Computational time for each normalization method to recognize the test image is shown in Table 2. Computational speed for Wavelet Denoising method is faster when compared with other techniques.

**Table 2: CPU Time for Recognizing Test Image**

| Methods | Time Taken for Recognizing Test Image (ms) |
|---|---|
| DCT | 970 |
| Wavelet | 690 |
| Gradient face | 840 |
| LCE | 880 |
| Weber faces | 940 |

## CONCLUSIONS

Various illumination normalization methods for face recognition have been implemented and their performance has been evaluated. Weber faces appear to be the best at handling illumination, with respect to recognition rate. Wavelet Denoising technique is computationally faster, but the recognition rate is less. The experiment has been performed by considering the center portion of the face. More discriminant features can be obtained if entire face image has been taken into account. This can help to maximize the interclass distance and improve the recognition rate.

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