

# Image Normalization Robust using Histogram Equalization and Logarithm Transform Frequency DCT Coefficients for Illumination in Facial Images

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**Abstract:** A new approach used for image normalization illumination under varying lighting conditions is presented. The discrete cosine transform (DCT) method is applied on the images captured under varying lighting conditions. Illumination variation is one of intractable crucial problems in face recognition and many lighting normalization approaches have been proposed in the past decades. Most of the illumination corresponds to low frequency region. Face recognition algorithms have to deal variations as well as various facial features of a human face dealing with variations between gallery and probe images. In this paper, we propose a scaling of low frequency DCT coefficients is utilized for normalization method, which performs adaptive preprocessing for each testing image according to its lighting attribute. A proper way of scaling low frequency DCT coefficients is utilized by illumination normalization. The images captured under varying illumination have low contrast. For contrast stretching the adaptive histogram equalization is applied on face images. The comparative results are provided to evaluate the imaging hardware, the face and eye detection algorithms, and the face recognition algorithms and systems, with respect to various factors, including illumination, eyeglasses, time lapse, and so on. To analyze our illumination normalization method, we have used Yale Face Database. The results show better appearance of images and have been discussed with other approaches.

**Keywords:** Adaptive Histogram Equalization, Discrete Cosine Transform, Face Recognition, Illumination Normalization, Logarithm Transform

## 1. Introduction

Face Recognition accuracy depends on how Facial images have been compensated for pose, illumination and facial expression. A human face image encodes much useful information, such as identity the person, detection of the face and emotion, which are significant for developing practical and humanoid computer vision systems. The problems of identity verification and emotion recognition have been extensively studied as conventional multi-classical images. The challenges that a face recognition system has to face include variations in lighting, head pose, facial expression, emotion and so on. Among these factors, varying lighting conditions such as shadows, underexposure and overexposure in face imaging are intractable and crucial problems that a practical face recognition system to deal with various method. Pattern recognition problems in the computer vision literature.

This method is simple and effective approach for illumination normalization of human facial, machine recognition systems have reached a certain level of maturity. The performance of current algorithms degrades significantly when tested across pose and illumination of facial image. The illumination problem is basically the variability of an object's appearance from one image to the next with slight changes in lighting conditions.

In this paper, we concentrate on the face recognition problem with a fixed frontal pose under varying lighting conditions. The large variations in the face appearance which can be much larger than the variation caused by personal identity. In the last decades, many approaches have been proposed to handle illumination variation problem with the goal of illumination normalization, illumination-

insensitive feature extraction or illumination variation modeling. Previous method shows in illumination invariant face recognition focused on image representations that are mostly insensitive to changes in illumination. The image representations include edge values, Gabor filters, gray-level image, and the logarithmic transformations of the intensity image. However, the image representations were found to be satisfactory to overcome variations due to illumination changes.



**Figure 1:** Images of the same person under different lighting expressions

The different approaches to solve the problem of illumination invariant face recognition can be solved problems and analyzing face expression.

## 2. Current Approaches of Illumination Processing in Face Recognition

Recently many research papers have been published to study on illumination processing in face recognition. These approaches can be divided into two categories; Active approach and passive approach. In active approach the problem by employing active imaging techniques to obtain face images captured in consistent of illumination invariant modalities. The passive approaches are divided into four groups: illumination invariant features, illumination variation modeling, photometric normalization, and 3D morphable model.

Our approach belongs to photometric normalization approach for compensating illumination variations. The representative methods of this category are histogram equalization, gamma intensity correction, logarithm transform, and etc. for illumination normalization [4]. But these global processing techniques of image processing are found to be insufficient to overcome variations due to illumination changes.



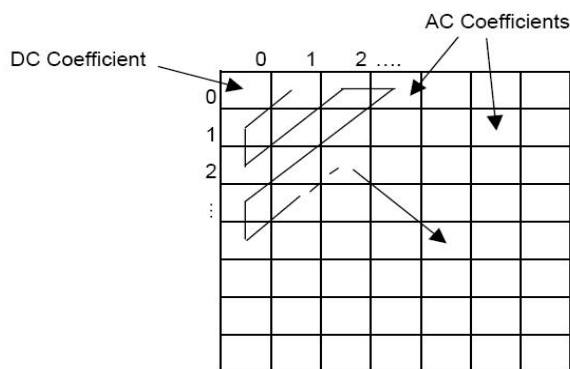
**Figure 2:** Images of the same person under different angle variation.

There are some methods which utilizes and enhancing the visual appearance of the images under varying illumination conditions. The low-frequency DCT coefficients rescaling are applied on the output of histogram equalized in input image. On a database of low illumination variations, histogram equalization for illumination compensation, while they have used low frequency DCT coefficients for feature extraction.

### 3. Adaptive Histogram Equalization with DCT Coefficients

#### 3.1 Adaptive Histogram Equalization

Histogram equalization maps the input image's intensity values so that the histogram of the resulting image will have an approximately uniform distribution.



**Figure 3:** Block feature of DCT coefficients and their selection in zigzag pattern.

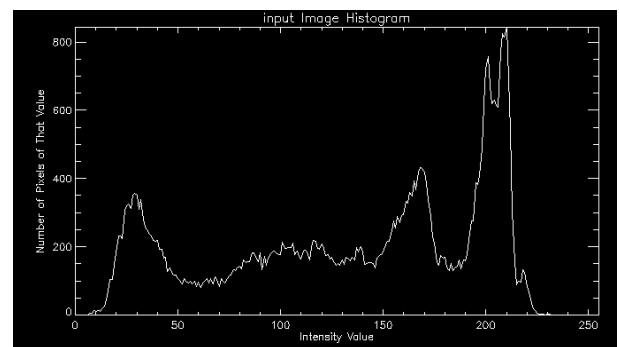
The histogram of a digital image with gray levels in the range  $[0, L-1]$  is a discrete function  $p(rk) = nk / n$  (1) where  $rk$  is the  $k^{\text{th}}$  gray level,  $nk$  is the number of pixels in the image with that gray level,  $n$  is the total number of pixels in the image, and  $k = 0, 1, 2, \dots, L-1$ . Basically  $p(rk)$  gives an estimate of the probability of occurrence of gray level  $rk$ .



**Figure 4:** Equalized input image

Histogram equalization, the local contrast of the object in the image is increased, especially when the applied data of the image is represented by close contrast values. The intensity can be better distributed on the histogram, through this adjustment. This allows for areas of lower local contrast to gain a higher contrast without affecting the global contrast. In histogram equalization, the goal is to obtain a uniform histogram for the output image, is an "optimal" overall contrast is perceived.

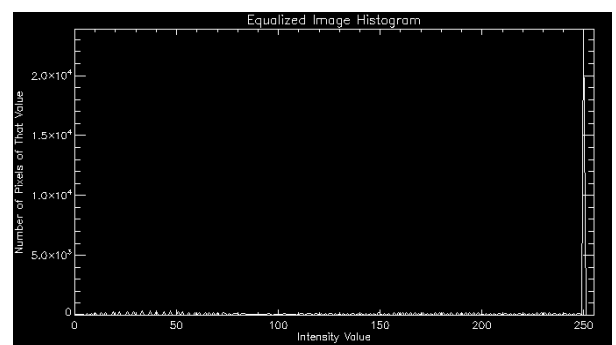
However, the feature of interest in an image might need enhancement locally. Adaptive Histogram Equalization (AHE) computes the histogram of a local window centered at a given pixel to determine the mapping for that pixel, which provides a local contrast enhancement.



**Figure 5:** Input Images of the same person Histogram equalization.

However, the enhancement is so strong that two major problems can arise: noise amplification in "flat" regions of the image and "ring" artifacts at strong edges [1].

A generalization of AHE, Contrast Limiting AHE (CLAHE) has more flexibility in choosing the local histogram mapping function. By selecting the clipping level of the histogram, undesired noise amplification can be reduced [5]. CLAHE operates on small regions in the image, (tile) rather than entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by a distribution parameter, which may be a uniform or a different shape histogram.



**Figure 6:** Input Images of the same person equalized Histogram

The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image. Figure 3 Block feature of DCT coefficients and

their selection in zigzag pattern. After applying adaptive histogram equalization, we employed logarithm transform [10] for further enhancement of the image.

### 3.2 Discrete Cosine Transform (DCT):

The DCT is a popular technique in imaging and video compression, which transforms signals from the spatial representation into a frequency representation. The forward 2D-DCT a  $M \times N$  block image is defined as

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

The inverse transform is defined as

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

$$\text{where } \alpha(u) = \begin{cases} \frac{1}{\sqrt{M}}; & u = 0 \\ \sqrt{\frac{2}{M}}; & u = 1, 2, \dots, M-1 \end{cases}$$

$$\alpha(v) = \begin{cases} \frac{1}{\sqrt{N}}; & v = 0 \\ \sqrt{\frac{2}{N}}; & v = 1, 2, \dots, N-1 \end{cases}$$

$x$  and  $y$  are spatial coordinates in the image block,  $u$  and  $v$  are coordinates in the DCT coefficients block. Fig.3 shows the properties of the DCT coefficients in  $M \times N$  blocks with the zigzag pattern used by JPEG image compression to process the DCT coefficients. Although the total energy remains the same in the  $M \times N$  blocks, the energy distribution changes energy being compacted to the low-frequency coefficients. We are taking the images A and B of same size. The average values of images A and B respectively. The correlation coefficient between two images can be used as a distance metric in the face recognition classifier engine.

## 4. Results and Discussions

The experimental result which contains Yale Face Database of 480 single light source images of 10 subjects each seen under 48 viewing conditions (4 poses x 12 illumination conditions). As we are analyzing the training face image same subject the illumination normalization consist of only frontal face images with illumination variation.



Figure 7: Deducted Image from different angle variation.

In figure 2 cropped images are categorized in four subsets based on the azimuth and elevation of the light source direction.



Figure 8: Cropped image and Small rectangle Deduction Image from deducted image.

Original size of the image after cropping image deducted in small size rectangle and the resolution of  $192 \times 168$  pixels. Fig. 1 shows the 5 individuals under uniform illumination from the Yale Face Database.

### A. Illumination Processing in Video-based Face Recognition

Video-based face recognition is being increasingly discussed and occasionally deployed. Face recognition in still, it has its own unique features, such as temporal continuity and dependence between two neighboring frames. In addition, it requires high real time in contrast to face recognition in still. Their differences are compared in Table 1.

Table 1: The comparison between face recognition in video and in still

Face Recognition in Video	Face Recognition in Still
Low resolution faces	High resolution faces
Varying illumination	Even illumination
Varying pose	Frontal pose
Varying expression	Neutral expression
Video sequences	Still image
Continuous motion	Single motion

Most existing video-based face recognition systems are realized the facial image. First face features extracted, detected and then tracked over time. Only when a frame satisfying such method (frontal pose, neutral expression and even illumination on face) is acquired, recognition is still. However, the uneven illumination on face always exists, which lead that we cannot find a suitable time to recognize the face. Using the same algorithms, the recognition result of video-based face recognition is not satisfying like face recognition in still. For example the video-based face recognition systems were set up in several places like, crowded places, station and airports around the International Airport.

However illumination processing algorithms can be applied for video-based face recognition, but we encounter three main problems at least: Video-based face recognition systems require higher real-time performance. Many illumination processing algorithms can achieve a very high recognition rate, but some of them take much more computational time.

### B. Illumination Normalization using Proposed Approach

A face image obtained under uniform illumination contains its histogram equalization. In histogram equalization try to achieve approximate uniform histogram for the processed image. To obtain histogram of input images, we apply adaptive histogram equalization with a distribution parameter as (a) Original Image with its histogram; (b) After histogram equalization; (c) After adaptive histogram equalization. Fig. 2(a) shows one of the images taken from database with its corresponding histogram.

Fig. 4 that the illumination variations are not affected, these remain in the images, although illumination variations are shifted to the upward in the gray scale. There are some facial features of an individual which correspond to the low-frequency DCT coefficients. Thus illumination normalization means to obtain the low-frequency DCT coefficients which correspond to the uniform lighting as well as to preserve the low-frequency details of a subject. This is done by dividing the first 21 low-frequency DCT coefficients by a constant value. We have shown output images of proposed approach along with other approach in Fig.4. The comparative study of proposed approach using correlation coefficient as matching score is also given in Table 1.

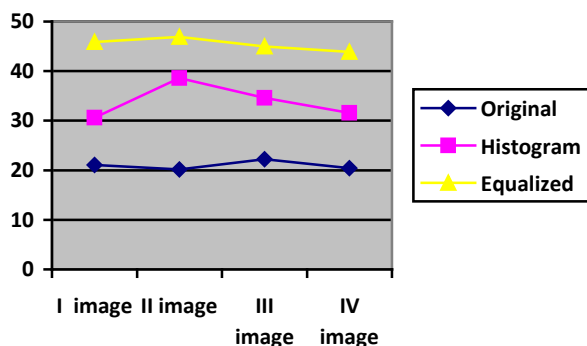


Figure 9: Comparison of input image

The linear fall in the recognition performance increased the value of image. Even when the training images are selected at random, the results still outperform standard histogram-fitting, gaining a high recognition rate of almost 92% shows the sum of test images with large illumination variation. The result of applying histogram equalization on test images is shown in Fig. 4(b). Similarly, the result of rescaling of low frequency. The value of correlation coefficient can vary from a negative value to highest possible value as one. Value one means accurate matching. So higher values of correlation coefficient imply better matching, hence better illumination normalization.

## 5. Conclusions

In this paper, we propose a novel approach for illumination normalization. It is based on adaptive histogram equalization, logarithm transform and down scaling of low-frequency DCT coefficients is proposed. The input image low-frequency DCT coefficients are scaled down for illumination compensation. The performance of the proposed approach is quite better for different illumination variation. There is significant improvement in the values of correlation coefficient over the value of that obtained using other methods. Thus better illumination normalization is achieved under all illumination variations. The obtained results in the present investigation may expand future prospects for real time and robust face recognition systems.

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