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.

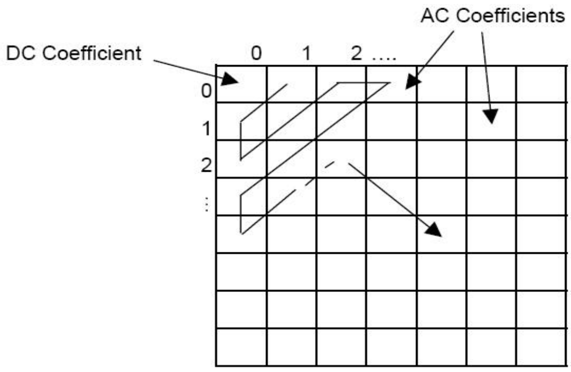

Figure 3: Block feature of DCT coefficients and their selection in zigzag pattern.

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^{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, …, *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.

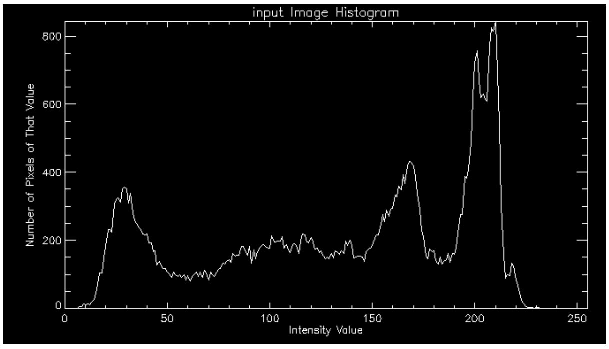

Figure 5: Input Images of the same person Histogram equalization.

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, (title) 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.

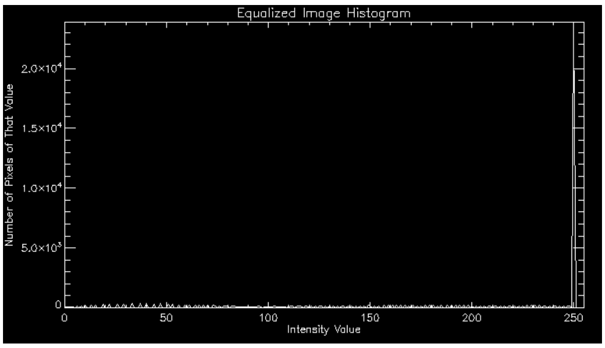

Figure 6: Input Images of the same person equalized Histogramn

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

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

The inverse transform is defined as

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

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

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

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 × 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.

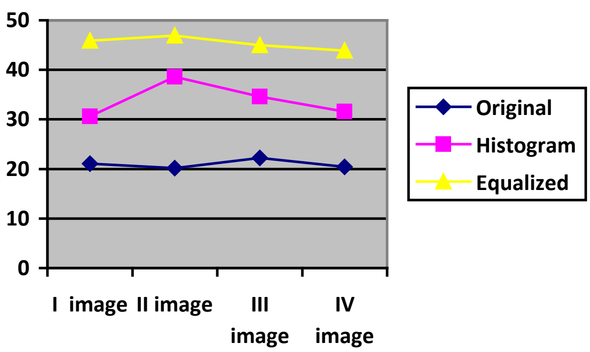

Figure 9: Comparison of input image

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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