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A Novel Approach for Face Recognition Using DCT Coefficients Re-scaling for Illumination Normalization

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***Abstract*-A novel approach for illumination normalization is proposed by exploiting the correlation of discrete cosine transform (DCT) low-frequency coefficients to illumination variations. The input image contrast is stretched using full image histogram equalization. Then the low-frequency DCT coefficients (except first) are re-scaled to lower value to compensate the illumination variations. The first (DC) coefficient is scaled to higher value for further contrast enhancement. The experiments are performed on the Yale B database and the results show that the performance of the proposed approach is better for the images with large illumination variations. The proposed technique is computationally efficient and can easily be implemented for real time face recognition system.**

I. Introduction

Face recognition is one of the most successful applications of image analysis and understanding. This has received significant attention, because of its wide range of commercial and law enforcement applications [1],[2]. Even though current machine recognition systems have reached a certain level of maturity, their success is limited by the conditions imposed by many real applications. For example, recognition of face images acquired in an outdoor environment with changes in illumination and/or pose remains a largely unsolved problem. Ambient lighting changes greatly within and between days and among indoor and outdoor environments. Due to the 3D structure of the face, a direct lighting source can cast strong shadows that accentuate or diminish certain facial features. The illumination problem is basically the variability of an object's appearance from one image to the next with slight changes in lighting conditions and viewpoint. This often results in large changes in the object's appearance [3],[4].

Early work in illumination invariant face recognition focused on image representations that are mostly insensitive to changes in illumination. There were approaches in which the image representations and distance measures were evaluated on a tightly controlled face database that varied the face pose, illumination, and expression. The image representations include edge maps, 2D Gabor-like filters, first and second derivatives of the gray-level image, and the logarithmic transformations of the intensity image along with these representations. However, none of the image representations was found to be sufficient by itself to overcome variations due to illumination changes [4].

The different approaches to solve the problem of illumination variation can be broadly classified into three main categories. The first approach is based on "preprocessing and normalization". The representative methods are histogram equalization (HE), Gamma correction, logarithm transform, etc. for illumination normalization. However, non-uniform illumination variation is still difficult to deal with using these global processing techniques [5]. In the second approach, the systems are exploiting "invariant feature extraction" method. A very renowned method for feature extraction is Fisher-face (based on linear discriminant analysis (LDA)), which maps the image space to a low dimensional subspace to discount variation in lighting etc.[6]. This method is a statistical linear projection method in which the representativeness of the training samples controls the performance of the system. The quotient image is regarded as the illumination invariant signature image, which can be used for face recognition under varying lighting condition [7]. Bootstrap database is required for this method and the performance degrades when dominant features between the bootstrap set and the test set are misaligned. The face modeling methods are under third category (3-D Shape of human faces) [5]. Here the attempt is to construct a generative 3-D face model that can be used to render the face images with different poses and lighting conditions. A generative model called illumination cone was presented in [8]. The main idea of this method is that the set of face images in fixed pose but under different illumination conditions can be represented using an illumination convex cone, which can be constructed from a number of images acquired under variable lighting conditions and the illumination cone can be approximated in a low-dimensional linear subspace.

In this paper, we propose a novel approach that utilizes the image enhancement capability of DCT. The full image histogram equalization method is applied for the given image for contrast stretching. To suppress illumination variations the DCT is applied on the resultant image. As the low-frequency DCT coefficients (except first) correspond to illumination variations, the authors propose a new technique to suppress them. The method involves the re-scaling of these coefficients. Also to achieve further contrast enhancement, the first (DC) coefficient is scaled to a higher value. The results show better appearance of images as compared to other existing approaches.

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II. CONTRAST STRETCHING AND ILLUMINATION NORMALIZATION IN DCT DOMAIN

A. Histogram Equalization

The histogram of a digital image with gray levels in the range [1, L] is a discrete function

$$p(r_k) = n_k / n, \quad (1)$$

where r_k is the kth gray level, n_k is the number of pixels in the image with that gray level, n is the total number of pixels in the image, and $k = 1, 2, \ldots, L$. Basically $p(r_k)$ gives an estimate of the probability of occurrence of gray level r_k.

By histogram equalization, the local contrast of the object in the image is increased, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensity can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast without affecting the global contrast. The histogram equalization is defined as a transformation on the input intensity levels (r_k) to obtain output intensity levels (s_k) as

$$s_k = T(r_k) = \sum_{j=1}^{k} p_r(r_j) = \sum_{j=1}^{k} \frac{n_j}{n} \quad (2)$$

for k = 1, 2,…, L.

B. Discrete Cosine Transform

The DCT is a popular technique in imaging and video compression, which transforms signals in the spatial representation into a frequency representation.

The forward 2D-DCT [5],[9] of a M x N block image is defined as

$$C(u,v) = \alpha(u)\alpha(v)\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y) \times \cos\left[\frac{\pi(2x+1)u}{2M}\right]\cos\left[\frac{\pi(2y+1)v}{2N}\right] \quad (3)$$

The inverse transform is defined as

$$f(x,y) = \sum_{u=0}^{M-1}\sum_{v=0}^{N-1} \alpha(u)\alpha(v)C(u,v) \times \cos\left[\frac{\pi(2x+1)u}{2M}\right]\cos\left[\frac{\pi(2y+1)v}{2N}\right] \quad (4)$$

where

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

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

and, x and y are spatial coordinates in the image block, and u and v are coordinates in the DCT coefficients block. Fig.1 shows the properties of the DCT coefficients in M x N blocks with the zigzag pattern used by JPEG compression to process the DCT coefficients. Although the total energy remains the same in the M x N blocks, the energy distribution changes with most energy being compacted to the low-frequency coefficients. The DC coefficient is represented by C(0,0) in the forward 2D-DCT equation. As the cosine of zero is one, the equation is simplified to:

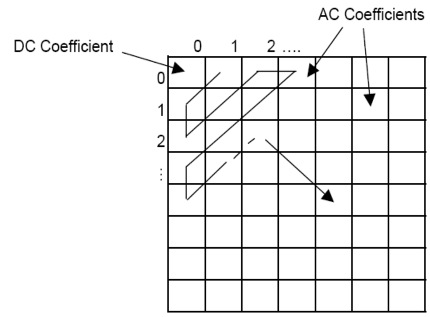

Fig.1 Block feature of DCT coefficients and their selection in zig-zag pattern.

$$C(0,0) = \frac{1}{M \times N}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y) \quad (5)$$

The DC coefficient, which is located at the upper left corner, holds most of the image energy and represents the proportional average of the M x N blocks. The remaining ((M x N) −1) coefficients denote the intensity changes among the block images and are referred to as AC coefficients. The DCT is performed on the entire image obtained after processing the input face images by histogram equalization.

III. EXPERIMENTAL RESULTS AND DISCUSSIONS

A. Face Database

The experiments are carried out on the Yale Face Database B [10] which contains 5760 single light source images of 10 subjects each seen under 576 viewing conditions (9 poses x 64 illumination conditions). For every subject in a particular pose, an image with ambient (background) illumination was also captured. We concentrated on the images with illumination variations. Some sample images are given in Fig.2.

B. Histogram Equalization

After applying histogram equalization on the images of face database, the contrast of the processed images is stretched to full range of intensity levels. Fig.3(a) shows one of the images taken from database and its corresponding histogram is shown in Fig.3(c). Fig.3(b) shows the processed image after applying histogram equalization on the image of Fig.3(a). The histogram of processed image is shown in Fig.3(d). The histogram of original image, as shown in Fig.3(b), depicts that the probability of occurrence of intensity levels is below the mid of gray scale. After histogram equalization, we obtain approximately uniform intensity distribution and we get a high contrast image as shown in Fig.3(b). But it is also visible from Fig.3(a) and Fig.3(b) that the illumination variations are not affected, these remain in the images, although illumination variations are shifted to the upward in the gray scale. This problem is solved by the method described in the next sub-section.

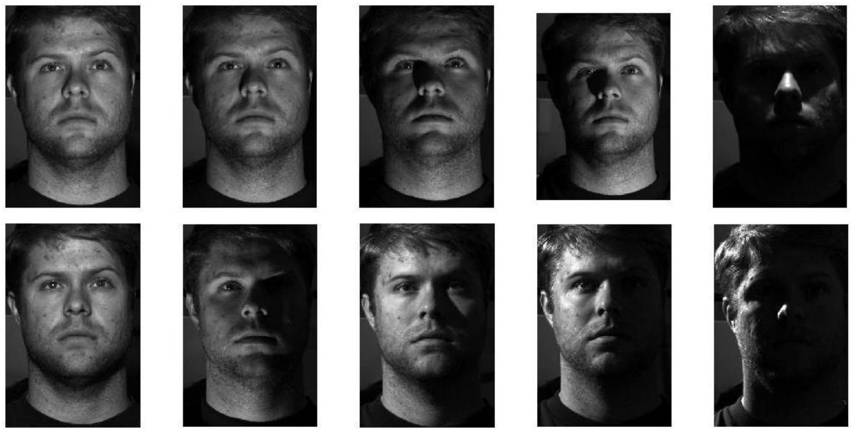

Fig. 2 Sample images of an individual under different illumination.

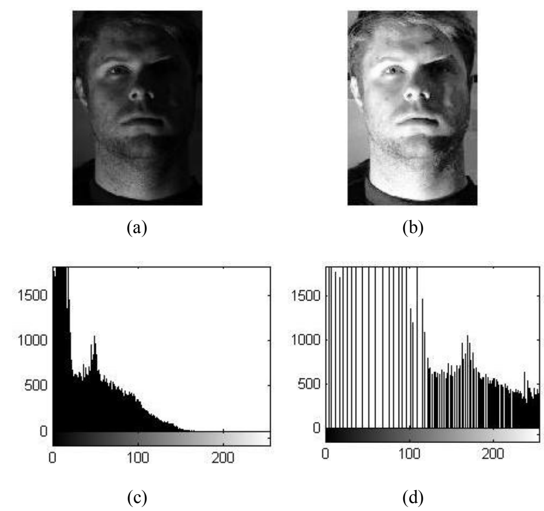

Fig. 3 (a) Original Image; (b) Image after histogram equalization; (c) Histogram of image in (a); (d) Histogram of image in (b).

C. Illumination Normalization using Re-scaling of Low-Frequency DCT Coefficients

Our approach for illumination normalization utilizes the fact that low-frequency DCT coefficients are correlated with illumination variations. As mentioned in Fig.1 the DCT coefficients are selected in zig-zag pattern, if we select DCT coefficients from upper diagonal elements of top-left corner of Fig.1, the DCT coefficients will be in increasing order of frequency (C_{resc}). For the images taken in analysis (Fig.2), the total number of DCT coefficients are 385*256 = 98560, out of these the coefficients corresponding to low frequencies are selected for re-scaling. Fig.4 shows the variation of appearance with the number of coefficients selected (C_{resc}). The Fig.4 (a) shows the original image, Fig.4(b) corresponds to image after histogram equalization only, Fig4(c)-(j) show the effect on illumination with variation of the number of DCT coefficients selected. It is evident from the Fig.4, that the optimal range of C_{resc} is between 20 to 54 (Fig.4 (e) to (g)). We have taken the lower value of C_{resc} as 20, to increase the computational efficiency of the system.

In the approach given by W. Chen et. al., [5], the low-frequency DCT coefficients are discarded. This results in loss of some information related with low-frequency DCT coefficients, which will be discussed in the next sub-section. In the proposed approach, we are dividing the low-frequency DCT coefficients by a constant 50. This value is taken by considering the ratio of C(0,0) of a properly illuminated image with that of a badly illuminated image (considered the last image of the samples in Fig.2).

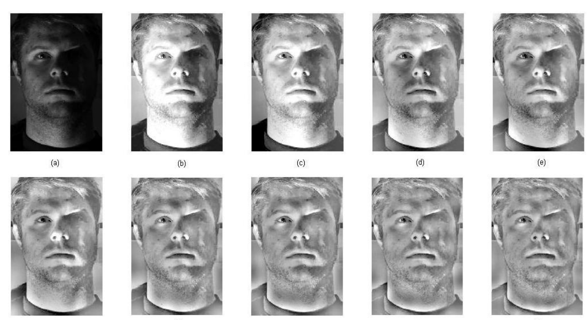

Fig.4 Normalized images with different C_{resc} : (a) original image; (b) only histogram equalization, $C_{\text{resc}} = 0$; (c) $C_{\text{resc}} = 2$; (d) $C_{\text{resc}} = 9$; (e) $C_{\text{resc}} = 20$; (f) $C_{\text{resc}} = 35$; (g) $C_{\text{resc}} = 54$; (h) $C_{\text{resc}} = 77$; (i) $C_{\text{resc}} = 104$; (j) $C_{\text{resc}} = 135$.

Fig.5 shows the images after applying the proposed approach on the images of Fig.2 after applying histogram equalization. We have taken the concept of re-scaling to lower value of the low-frequency DCT coefficients, which is done by dividing these coefficients by the constant discussed above. Because the illumination variations are directly related with the low-frequency DCT coefficients.

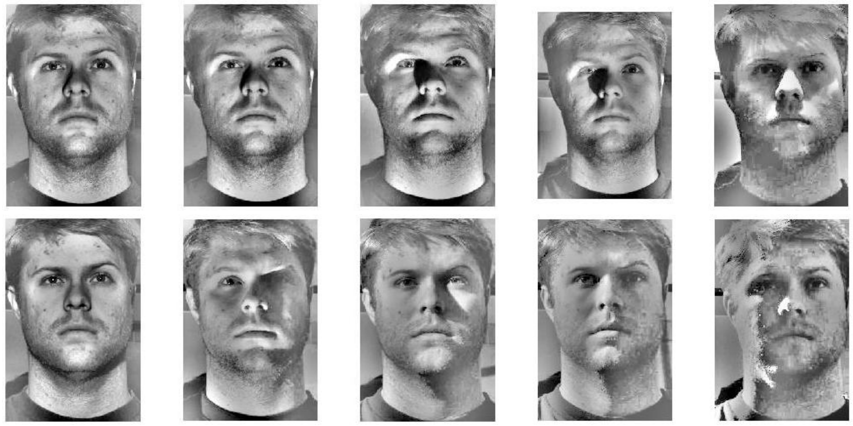

Fig.5 Output images after applying the proposed approach

(a)

(b)

(c)

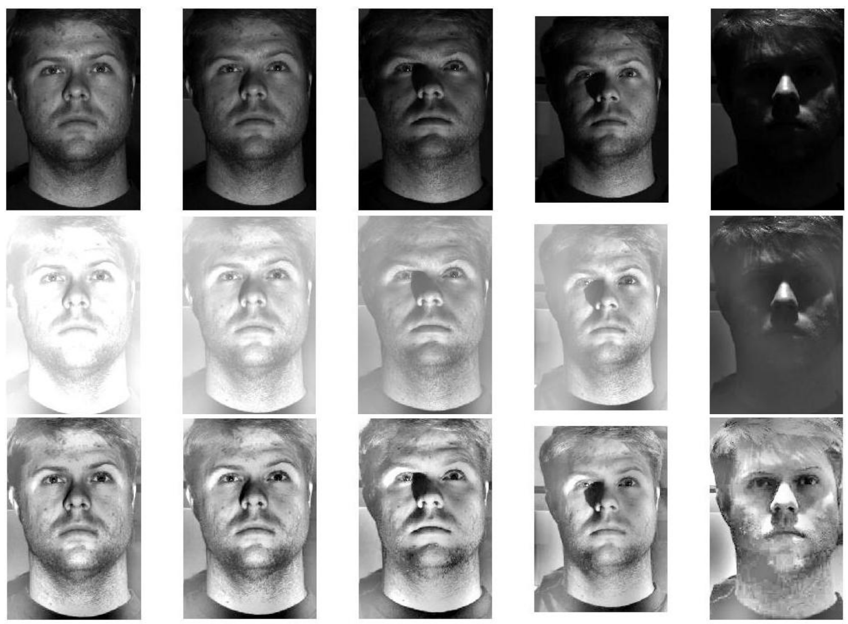

Fig.6 Comparison of output images (a) original images; (b) The output images of the approach given by W. Chen et. al., [5], after applied on the images of (a);
(c) The output images of the proposed approach after applied on the images of (a).

But there are some facial features which correspond to the low-frequency DCT coefficients, so we can not completely discard them (as done by W. Chen et. al., [5]). That is why we re-scale these coefficients and better results are obtained as shown in Fig.6.

Another modification is proposed in our approach. As for optimal result, we divide the first 20 low-frequency DCT coefficients by a constant (50), when we apply the inverse DCT, the contrast of the image obtained is lower. To overcome this problem, before applying inverse DCT, we increase the DC coefficient C(0,0) by 10%. This results in further contrast enhancement of the output image.

D. Comparison with other approach

In Fig.6 the comparative study of the approach given by W. Chen et. al., [5] is done with the proposed approach. The Fig 6(a) shows the original images with illumination variation. The result of discarding first 20 low-frequency DCT coefficients for respective input images are shown in Fig.6(b). The fading effect of images in Fig.6(b) is also visible. The Fig.6(c) shows the output of applying the proposed approach for respective input images taken in Fig.6(a). It is evident from these figures that the performance of the proposed approach is quite better for different illumination variation. Another advantage of our approach is that for different illuminated images, it does not require recalculation of DC coefficient.

IV. CONCLUSIONS

In this paper, we propose a novel approach for illumination normalization. The input image contrast is stretched using full image histogram equalization. The low-frequency DCT coefficients are re- scaled to suppress the illumination variations. The appearance of output images of the proposed approach compared to that of the other approaches is better. Hence the proposed technique can be implemented in real time face recognition system. The present research shows that the effect of shadowing is not eliminated. In our future work we will focus on the elimination/reduction of shadowing effect.

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