Illumination Normalization based on 2D Gaussian illumination model

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Abstract—**Achieving illumination invariance in the presence of varying lighting conditions remains one of the most challenging aspects of automatic face recognition. In this paper, a novel approach for illumination normalization under varying lighting conditions is presented. This method is based on a 2D Gaussian illumination model, which is first proposed in this paper. This model can be used for contrast stretching in the "dark" areas on the face images. In our method, we choose Quadtree to o locate the shadows, and then apply the 2D Gaussian illumination model to adjust contrast of these dark areas, last utilize the symmetrical property of human face to obtain the illumination invariance features of the face images. The proposed algorithm has been evaluated based on the Yale B database. The experimental results show that our algorithms can significantly improve the performance of face recognition under uneven illumination conditions.**

Keywords-illumination; Gaussian function; face recognition; PCA; Quadtree

I. INTRODUCTION

Face recognition has received a great deal of attention over the last few years because of its usage covers many applications in various domains, such as security surveillance, general identity verification, image database investigations and etc. [1]. For many applications, the performance of face recognition systems in controlled environments has reached a satisfactory level. However, majority of existing face recognition techniques such as Principal component analysis (PCA) [2] still exhibit a significant drop in their recognition performance in the presence of illumination variation [3]. This is because that the variations between the images of the same face due to illumination and viewing directions are almost always larger than the image variations due to a change in face identity [4].

To cope with face variations caused by illumination, a number of illumination invariant face recognition approaches have already been proposed in the past years. Jobson et al. [5] [6], for example, achieved illumination invariance through the illumination-reflection model. The model assumes that each image can be represented as a product of illumination and reflectance, where illumination represents the amount of measured light intensities and reflectance denotes the amount of light reflected by a given object. In their approaches, the luminance is estimated by the smoothed image. The image can be divided by the luminance to obtain the reflectance, which is an invariant feature to illumination. A single Gaussian function is applied to smooth the image in [5], and the sum of several Gaussian functions with different scales is applied in [6]. Based on Jobson et al. work, Wang et al. [7] defined self-Quotient image, this method performs illumination subtraction without the need for alignment and no shadow assumption. Zhang et al. [8] proposed a morphological Quotient Image method in which mathematical morphology operation is employed to smooth the original image to obtain a luminance estimate.

Recently, Štruc et al. [9] proposed Histogram Remapping method which remaps the histogram of a given facial image to the target distributions: the uniform, the normal, the lognormal and the exponential distribution. However, the parameters for the given target distribution is not determined automatically. Heng Fui Liau and Dino Isa [10] presented a preprocessing method based on the discrete cosine transform (DCT). The proposed technique can correct the shadows and specula defects to some extent by manipulating the odd and even DCT components, but it is unable to completely remove artifacts that appear on the both sides of the face. This causes the method to have rather unimpressive performance in some condition compared to the DCT in logarithm domain method [11].

In this paper, a novel illumination compensation method for human face recognition is proposed. In our method, we admit the fact that shadow effects are mainly caused by the small intensities on the corresponding position. Based on this fact, the illumination invariance can be compensated by increasing the intensities at the dark areas through the 2D Gaussian illumination model, which is firstly proposed in this paper. Facial symmetry can be regarded as a not absolute but useful and natural feature. Accounting for the possibility of over compensation in the bright areas, this symmetrical feature is also imported to obtain the illumination invariant features. Then the generated images, which are insensitive to illumination variance, are used for face recognition using PCA method. Experimental results on Yale face database B [12] show that the proposed method has achieved good performance as compared to some of the methods described above.

This paper is organized as follows. In Section 2, 2D Gaussian illumination model adopted in this paper is introduced. Our method for implementing illumination invariant face recognition is presented in Section 3. In

Section 4, experimental results are detailed and the uses of different illumination normalization algorithms with PCA method based on Yale face database B are evaluated. Finally, in Section 5, conclusions are drawn.

II. 2D GAUSSIAN ILLUMINATION MODEL

Two-dimensional Gaussian function is widely used in image processing, where 2D Gaussian function is usually used for Gaussian blurs, the equation of this function is:

$$G(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{(x-a)^2+(y-b)^2}{2\sigma^2}} \quad (1)$$

Where a, b is the center, x is the distance from a in the horizontal axis, y is the distance from b in the vertical axis, and σ is the standard deviation of the Gaussian distribution.

In image processing, we need to compute the discrete approximation of a 2D Gaussian function through sampling the continuous Gaussian. In theory, the Gaussian function at every point on the image will be non-zero, meaning that the entire image would need to be included in the calculations for each pixel. But in practice, when computing a discrete approximation of the 2D Gaussian function, pixels at a distance of more than 3σ are small enough to be considered effectively zero. Thus contributions from pixels outside that range can be ignored. After these Computations, the discrete approximation of the 2D Gaussian function produces a surface, whose contours are concentric circles with a Gaussian distribution from the center point, The center pixel's value has the highest value and neighboring pixels has smaller values as their distance to the original pixel increases.

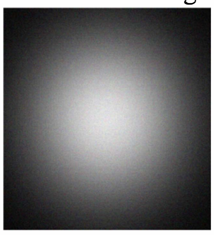
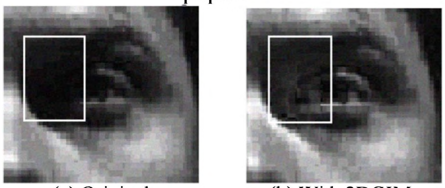


Figure 1. 2D Gaussian illumination model

In this paper, we use the 2D Gaussian function to model a vertical illumination and assume that the shadows in the face image can be considered as the lack of light in the corresponding areas. Based on this assumption, we proposes a new illumination compensation method, which compensates the shadow effects of varying lighting on a human face image through increasing the values in the dark areas using our 2D Gaussian illumination model. Fig.1 gives the 2D Gaussian illumination model (2DGIM).

As can be seen in the Fig.1, if we apply this illumination model to eliminate the shadow effects in the face images, it will increase the pixel values larger in the center than around, this character accords with our visual sensation.

Fig.2 illustrates an original image in the Yale B database and the corresponding image processed by the 2D Gaussian illumination model in this paper.



(a) Original. (b) With 2DGIM

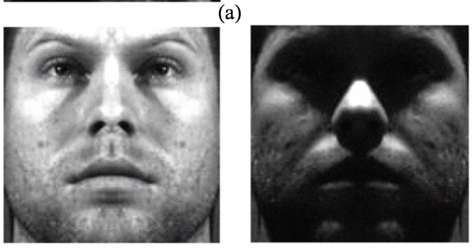
Figure 2. example of the 2DGIM

The figure shows that the 2D Gaussian illumination model tends to extract the features hided in the dark areas. It is less destructive of the surrounding features. This is because the 2D Gaussian illumination model well inherits the "continuity" of the 2D Gaussian function, and will not produce abrupt changes in the processing image. Therefore, from Fig.2 (b), we can see that the 2D Gaussian illumination model can not only reduce the local uneven lighting effect, but also retain the original boundary shape of foreground.

III. METHOD

In this section, we will introduce a method for implementing illumination invariant face recognition based on 2D Gaussian illumination model.

(a)



(b)

Figure 3. Samples of cropped faces and results used the symmetrical property of human face (a)the origina images, (b)the results

Human faces generally have symmetry property, if the illumination only affects the half side of the face, we can easily compensate the illumination variation through flipping the image in vertical position and adding to the original image. But when the illumination effect becomes larger, the shadows are still difficult to deal with only by using the symmetrical property of human face. These results are shown in Fig.3, compared with the left image in (a), the left image in (b) has removed the shadows, and in contrast, the right image in (b) also has shadows in the areas surrounding the eyes. As we can see, it is impracticable that we only use the facial symmetry to obtain the illumination invariant features in practice. In order to solve these problems, we have to find out other methods to cooperate with the symmetry property.

As aforementioned before, we can use the 2D Gaussian illumination model to reduce lighting effect. But how to locate the shdows? In this paper, we adopt the Quadtree [13] to solve this problem. Firstly, we choose a fixed value, which is specified as a value between 0 and 1, Then we divide the face image into four equal-sized square blocks if the image meets the criterion that the maximum value of the block elements minus the minimum value of the block elements is greater than the fixed value. If a block meets this criterion, it is not divided any further. If it does not meet the criterion, it is subdivided again into four blocks, and the test criterion is applied to those blocks. This process is repeated iteratively until each block meets the criterion. The result may have blocks of several different sizes. Lastly, we locate the center of the "dark" blocks in turn and construct a 2D Gaussian illumination model with the same size as the block, then multiply the cooresponding block in the original image , which has the same center as the chosen "dark" block, by this 2DGIM point to point to remove the shadows by increasing the pixel values. We choose the right image in Fig.3.(a) as the original face image, and Fig.4.(a) shows the the Quadtree decomposing shape. the result after removing the shadows and symmetrically processing is shown in Fig.4.(b). Compared with the right image in Fig.3.(b), the features of the eyes are more legible in Fig.4.(b).

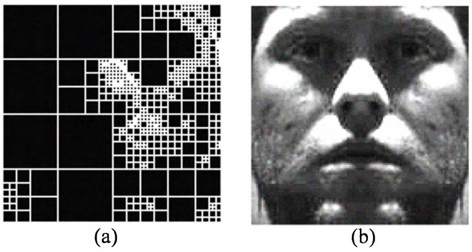


Figure 4. improvement using 2DGIM, (a) Quadtree decomposing, (b)the result after removing the shadows

The flow of the proposed illumination invariant face recognition system can be summarized as below:

a) Locate the shdows using the Quadtree.

b) Perform 2DGIM on the dark blocks in the face images to increase the pixel values in the dark areas.

c) Flip the image and add the two images to extract the illumination invariance features.

d) The generated images, which are insensitive to illumination variations, are used for face recognition.

IV. Experiment Results

In the experiments, we compare the performance of the proposed 2DGIM-based algorithm with other well-known illumination normalization algorithms using the standard face database.

A. *Face Database Used*

We will evaluate the performance of the 2DGIM algorithm for face recognition based on the Yale face database B in this section. The database, which contains 10 individuals in nine different pose. For each pose, there are 64 different illumination conditions, is often used to investigate the effect of lighting on face recognition. We only choose the images in frontal pose from the Yale B database. Then the chosen images are cropped and normalized to a size of 128×128 pixels, and aligned based on the two eyes. The cropped face images are divided into 4 subsets according to the angle the light source direction makes with the camera axis [14]: subset 1 (up to 12°), subset 2 (up to 25°), subset 3 (up to 50°), and subset 4 (up to 77°). In our experiment, subset 1 and subset 2 are used for training and the subset 3 and subset 4 for testing.

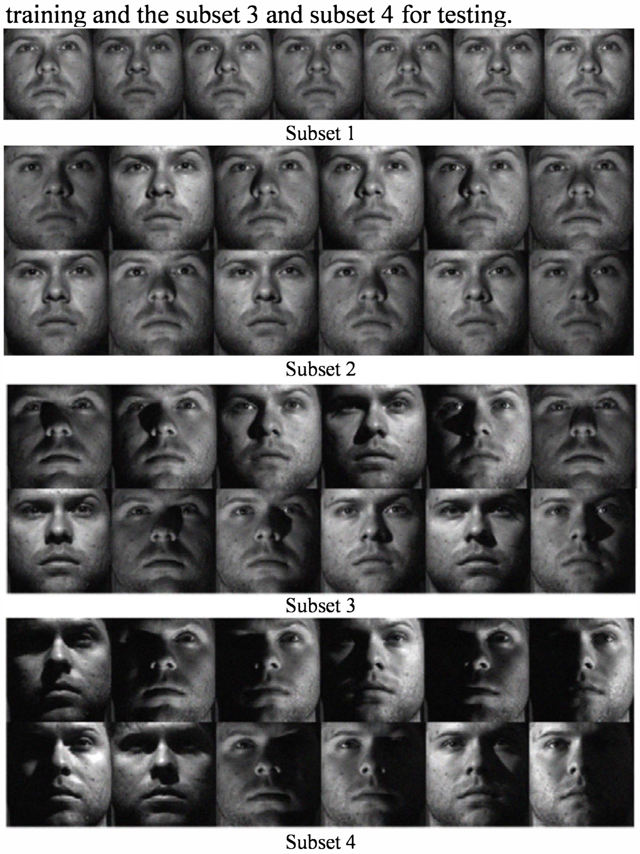


Figure 5. Four subsets images of a signal individual from the YaleB

B. *Face recognition using PCA*

Principal Component Analysis (PCA) is a classical method of human face representation and recognition. It can find out a set of projection vectors , which projects the input data in such a way that the covariance matrix of the training datas is maximized. In other words, it can transform a number of possibly correlated images into a smaller number of uncorrelated images called eigenfaces [15]. In the experiments, all images in subset 1 and subset 2 are selected to serve as training images to build the covariance matrix for PCA. Eigenvalue decomposition is applied on the covariance matrix to seek for the eigenfaces that projected the face images in the direction that maximized the covariance matrix. we adopt the Nearest Neighbor classification (NNC) with the Euclidean distance as the distance metric to classify the face images. In our experiment, the subset 1 and subset 2 are used for training, while the remaining subsets are employed for testing. Such an experimental setup will result in highly miss-matched conditions for the verification procedure and posed a great challenge to the processing techniques.

Table1 shows that our method can achieve a better performance level than if no illumination normalization is used. Without illumination normalization, the PCA method is only able to achieve 83.33% and 34.17% recognition rate in subset 3 and subset 4 respectively. The poor results are due to the large lighting variation, which causes dark areas in the faces. As we increased the values of the dark region with our method, it gives the good performance that recognition rate can reach 100% in subset 3 and 88.50% in subset 4.

TABLE I. FACE RECOGNITION

Method	**Recognition rate**	
	Subset 3	***Subset 4***
Original	83.33%	34.17%
Proposed method	100%	88.50%

C. Comparison with other method

In Table 3, the recognition rats on Yale Face Database B using other existing methods dealing with illumination normalization are presented along with the proposed approach. From Table 3, it is shown that all methods have larger recognition rate for subset 3 compared to the rate for subset 4. But our algorithm can improve the performance of PCA tremendously in subset 4, and the recognition rate can score 88.50%, which is larger than other methods.

TABLE II. COMPARISON WITH OTHER METHODS

Method	**Recognition rate**	
	Subset 3	***Subset 4***
Histogram equalization[16]	100%	75.83%
Histogram rmapping[9]	99.17%	81.67%
DCTmethod[10]	90.83%	36.67%
self-Quotient[7]	95%	48.33%
Proposed method	100%	88.50%

Our experiments were implemented in a personal computer with AMD Athlon™ II Processor and 1.75G RAM and Matlab version 7 (R14) was used.

V. CONCLUSIONS

In this paper, a novel illumination normalization method for human face recognition under varying lighting conditions is proposed. We use the Quadtree to locate the dark areas, and then use the 2D Gaussian illumination model and the symmetrical property of human faces to eliminate the shadows. Last, the generated images are used for face recognition. We evaluate our algorithm on Yale Face database B, the experimental results show that our method can receive very competitive recognition rates under uneven illumination conditions.

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