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The discrete cosine transform (DCT) plus local normalization: a novel two-stage method for de-illumination in face recognition

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To deal with illumination variations in face recognition, a novel two-stage illumination normalization method is proposed in this paper. Firstly, a discrete cosine transform (DCT) is used on the original images in logarithm domain. DC coefficient is set based on the average pixel value of all the within-class training samples and some low frequency AC coefficients are set to zero to eliminate illumination variations in large areas. Secondly, local normalization method, which can minimize illumination variations in small areas, is used on the inverse DCT images. This makes the pixel values on the processed images be close to or equal to that of the normal illumination condition. Experimental results, both on Yale B database and Extended Yale B database, show that the proposed method can eliminate effect of illumination variations effectively and improve performance of face recognition methods significantly. The present method does not demand modeling step and can eliminate the effect of illumination variations before face recognition. In this way, it can be used as a preprocessing step for any existing face recognition method.

Keywords: face recognition, discrete cosine transform (DCT), local normalization method, de-illumination, retinex theory.

1. Introduction

Face recognition has received significant attention because of its wide range of applications [1, 2]. Many existing face recognition algorithms are suitable for normal illumination conditions [3, 4]. However, in many cases, the same object may appear greatly different under varying illumination conditions and variations between images of the same face because of illumination are always larger than the image variations [5]. That is, difference caused by illumination conditions may be greater than the difference between classes. Face recognition under uneven illumination conditions is a challenging problem and many researchers have focused on the robustness of face recognition algorithms for varying illumination conditions. The approaches concerning this problem can be generally classified into 3 categories: invariant feature extraction, face modeling and illumination normalization.

The first method is to extract features which are invariant to illumination variations. The idea is direct and it is easily understood. ADINI *et al.* [5] used edge maps, derivatives of the gray-level and Gabor-like filters as invariant features. Linear discriminant analysis [6] was another famous feature extraction method and it could project an image into a low-dimensional subspace to discard variations caused by illumination. The gradient direction of an image was regarded as invariant feature by CHEN *et al.* [7]. SHASHUA and RIKLIN-RAVIV [8] used the quotient image as the illumination invariant image to solve the recognition problem under varying lighting conditions. However, ADINI *et al.* [5] had concluded based on theory and experiments that all the representations were insufficient by themselves to overcome the variations due to illumination.

The second method is to limit illumination variations into a subspace and model these variations in this subspace. The linear subspace related methods [9, 10] regarded face image as a Lambertian surface and three or more images of a subject under different illumination conditions can be used to construct the 3D illumination subspace. BELHUMEUR and KRIEGMAN [11] and GEORGHIADES *et al.* [12] proposed a generative model named illumination cone, in which it was considered that the set of face images with fixed pose and different illumination conditions can be represented by an illumination convex cone. BASRI and JACOBS [13] proved that a 9D linear subspace could approximate the images of a convex Lambertian object under varying illumination conditions. The performance of this kind of approaches is relatively good but it is difficult to be realized for the following reasons. Firstly, many images of an object under varying illumination conditions are needed during the training process. Secondly, this kind of approaches regard that the human face as a convex object and the casting shadows are not considered.

The third method is to preprocess the images under different illumination conditions to normalize them. Histogram equalization related methods [14] and Gamma correction [15, 16] have been widely used as a preprocessing course for illumination normalization. WEI YI ZHAO and CHELLAPPA [17] proposed SFS (shape from shading) method to reconstruct shape of a face based on the estimation of the lighting direction and albedo of the face. SHIGUANG SHAN *et al.* [18] introduced a method named quotient illumination relighting into face recognition under varying illumination conditions and the performance was relatively good. Local normalization method [19] was used as a preprocessing step to cope with illumination variations. The main advantage of this kind of method is that they can be used as a preprocessing step for any existing face recognition method.

In this paper, we focus on the third method and seek to improve the face recognition rate under varying illumination conditions. Retinex theory, logarithm method, discrete cosine transform (DCT) and local normalization method are used in this paper. To eliminate illumination variations in large areas, DCT is used on the original images in logarithm domain. DC coefficient is set based on the average pixel value of all the within-class training samples and some low-frequency AC coefficients are set to zero. In the second stage, local normalization method, which can minimize illumination variations in small areas, is used on the inverse DCT images. This method benefits from the state-of-the-art illumination normalization methods in two aspects. One is the setting of DCT DC coefficient and some AC coefficients, and the other is that it allows the use of local normalization method in the second stage. The proposed method is used in face recognition and the experimental results are encouraging.

The remainder of the paper is organized as follows. In Section 2, a complete two--stage method: DCT plus local normalization is proposed and framework of this method is given. In Section 3, experiments are performed on Yale B and Extended Yale B face database whereby the proposed algorithm is evaluated and compared to other methods. Finally, conclusions and discussion are offered in Section 4.

2. Framework of the two-stage de-illumination method

2.1. De-illumination in large areas based on DCT

DCT is a widely used orthogonal transform and it can transform an image from spatial domain to frequency domain. For an image $f(x, y)$ with size $M \times N$, DCT and the inverse transform are respectively defined as [20]

$$F(u, v) = c(u)c(v)\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x, y)\cos\frac{(2x+1)u\pi}{2M}\cos\frac{(2y+1)v\pi}{2N} \tag{1}$$

$$f(x, y) = \sum_{u=0}^{M-1}\sum_{v=0}^{N-1} c(u)c(v)F(u, v)\cos\frac{(2x+1)u\pi}{2M}\cos\frac{(2y+1)v\pi}{2N} \tag{2}$$

where $u = 0, 1, 2, ..., (M-1)$; $v = 0, 1, 2, ..., (N-1)$; $x = 0, 1, 2, ..., (M-1)$; $y = 0, 1, 2, ..., (N-1)$; $c(u) = \begin{cases} 1/\sqrt{M}, & u = 0 \\ \sqrt{2/M}, & 1 \le u \le M-1 \end{cases}$, $c(v) = \begin{cases} 1/\sqrt{N}, & v = 0 \\ \sqrt{2/N}, & 1 \le v \le N-1 \end{cases}$.

From retinex theory [21, 22], we know that the image $f(x, y)$ consists of the reflectance image $R(x, y)$ and the illumination image $L(x, y)$. That is,

$$f(x, y) = R(x, y)L(x, y) \tag{3}$$

Transforming Eq. (3) into the logarithm domain the following equation can be obtained

$$\log\left[R(x, y)\right] = \log\left[f(x, y)\right] - \log\left[L(x, y)\right] \tag{4}$$

From Eq. (4), we can conclude that the image with normal illumination can be obtained from the original image by subtracting the illumination image in logarithm domain. Research and experiments have proved that image variations caused by illumination mainly concentrate in the low frequency [23, 24]. In this way, variations caused by illumination can be compensated by discarding some low frequency components, which can be realized by setting some low frequency coefficients to zero. Setting some low frequency DCT coefficients to zero is equivalent to subtracting product of the DCT basis image and the corresponding DCT coefficients from the original image. We define $T(u, v)$ as

$$T(u, v) = c(u)c(v)F(u, v)\cos\frac{(2x+1)u\pi}{2M}\cos\frac{(2y+1)v\pi}{2N} \tag{5}$$

The following equation can be obtained from Eqs. (2) and (5) if some DCT coefficients are set to zero

$$f'(x, y) = \sum_{u=0}^{M-1}\sum_{v=0}^{N-1} T(u, v) - \sum_{i=1}^{n} T(u_i, v_i) = f(x, y) - \sum_{i=1}^{n} T(u_i, v_i) \tag{6}$$

Here, $f'(x, y)$ can be taken as the illumination-normalized image in the logarithm domain if $\sum_{i=1}^{n} T(u_i, v_i)$ is regarded as the illumination term. In this way, setting some low frequency DCT coefficients to zero is equivalent to eliminating the effect of illumination variations. To be easily computed and described, the number of DCT coefficients discarded is taken as the side-length of the isosceles triangle on the left--top of the DCT coefficients matrix. That is, if the number of DCT coefficients discarded is described as m in this paper, it corresponds to the first $m(m+1)/2$ DCT coefficients. Considering that DC coefficient controls the overall illumination of an image, we set it to a certain value as Eq. (7) instead of setting it to zero. In Equation (7), $F(0, 0)$ is DC coefficient, P is the number of within-class training samples and μ is the average value of the within-class training samples,

$$F(0, 0) = \log(\mu)\sqrt{MN} = \log\left[\frac{1}{PMN}\sum_{t=1}^{P}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x, y)\right]\sqrt{MN} \tag{7}$$

2.2. De-illumination in small areas based on local normalization method

Most of the illumination variations are normalized after the setting of DCT coefficients. However, face surfaces are not ideal Lambertian surfaces and illumination variations are not limited in the low frequency band strictly. That is, some illumination variations in some small areas cannot be eliminated completely by discarding some AC coefficients in low frequency. A face image can be divided into small facets and the area of each facet can be considered as a planar patch if it is small enough. Suppose

$g(x, y)$ and $g'(x, y)$ are the pixel values at (x, y) under normal illumination s and certain illumination s'. The illumination ratio image [25] in a facet can be given as

$$R_i = \frac{g'(x, y)}{g(x, y)} = \frac{\rho(x, y)n(x, y)^T s'}{\rho(x, y)n(x, y)^T s} = \frac{n(x, y)^T s'}{n(x, y)^T s} = \alpha, \quad (x, y) \in W \tag{8}$$

where $n(x, y)$ is the surface normal direction at the point (x, y) and $\rho(x, y)$ is the corresponding albedo. The relationship between $g(x, y)$ and $g'(x, y)$ can be described as Eq. (9) if the effect of noise δ at (x, y) is taken into consideration. For a small facet, α and δ can be considered as fixed values under a certain illumination condition

$$g'(x, y) = \alpha g(x, y) + \delta \tag{9}$$

Then we have

$$E(g'(x, y)) = E(\alpha g(x, y) + \delta) = \alpha E(g(x, y)) + \delta, \quad (x, y) \in W \tag{10}$$

$$\begin{aligned} \mathrm{Var}(g'(x, y)) &= \sqrt{\frac{\sum\left[g'(x, y) - E(g'(x, y))\right]^2}{M}} = \\ &= \alpha \sqrt{\frac{\sum\left[g(x, y) - E(g(x, y))\right]^2}{M}} = \\ &= \alpha \mathrm{Var}(g(x, y)), \qquad (x, y) \in W \end{aligned} \tag{11}$$

where M is the number of the pixels within facet W, $E(g(x, y))$ is the local mean of the pixels within facet W and $\mathrm{Var}(g(x, y))$ is the corresponding local variance under the normalized illumination. $E(g'(x, y))$ and $\mathrm{Var}(g'(x, y))$ are the local mean of the pixels and the corresponding variance under a certain illumination condition.

The idea of local normalization method is to get $s(x, y)$ whose mean is zero and variance is a unity by processing $g'(x, y)$ in a facet W. $s(x, y)$ is defined as follows

$$s(x, y) = \frac{g'(x, y) - E(g'(x, y))}{\mathrm{Var}(g'(x, y))} \tag{12}$$

It can be proved that $s(x, y)$ satisfies the limitation of zero mean and unit variance. From Eq. (10) to Eq. (12), we have

$$s(x, y) = \frac{g(x, y) - E(g(x, y))}{\mathrm{Var}(g(x, y))}, \quad (x, y) \in W \tag{13}$$

After local normalization processing, the image $g(x, y)$ under normal illumination can be described as

$$g_s(x, y) = \frac{g(x, y) - E(g(x, y))}{\mathrm{Var}(g(x, y))}, \quad (x, y) \in W \tag{14}$$

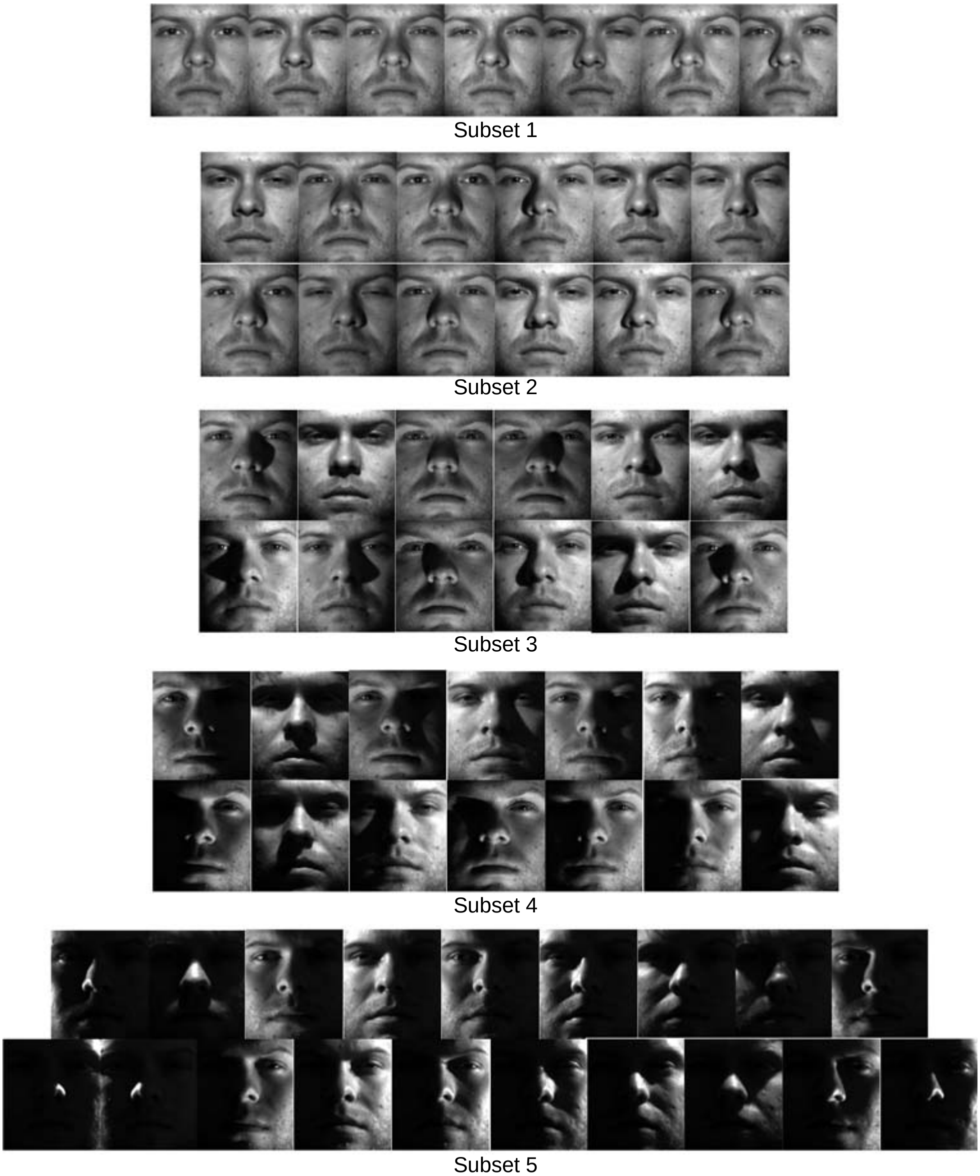

Fig. 1. Frontal face images of a subject in Yale B database and the sub-databases.

From Equations (13) and (14), we have

$$s(x, y) = g_s(x, y) \tag{15}$$

That is, after local normalization processing, pixel values of an image under a certain illumination will be equal to the values of the image under normal illumination condition. After the second stage of local normalization processing, illumination variations in small areas can be eliminated effectively.

3. Experiments

3.1. Face database

Yale B database and Extended Yale B database will be used to evaluate performance of the algorithm proposed in this paper. There are 10 subjects in Yale B database and each has 576 images obtained from 9 poses and 64 different illumination conditions. Extended Yale B database is extended from Yale B database and the number of people is 38. To test the de-illumination effect of our method, we choose the frontal face images (pose00) in our experiment and normalize them to the size of 96×84. The 64 images with frontal pose are divided into 5 subsets according to the angle of the light--source with respect to the optical axis of the camera: subset 1 ($\theta < 12°$), subset 2 ($20° < \theta < 25°$), subset 3 ($35° < \theta < 50°$), subset 4 ($60° < \theta < 77°$) and subset 5 ($85° < \theta < 128°$), which are shown in Fig. 1.

3.2. Number of discarded DCT coefficients

We select 20 subjects from Extended Yale B database to evaluate recognition performance based on different number of discarded DCT coefficients. For each subject, we choose 8 images from the 5 subsets randomly to form training sets and choose 32 images from the remaining 56 images randomly to form testing sets. That is, there are 160 training images and 640 testing samples in this experiment. Recognition performance with Euclidean distance method and PCA based on different number of discarded DCT coefficients are shown in Figs. 2**a** and 2**b**, respectively. In this experiment, the features used with Euclidean distance are pixel values. For PCA, the distance used is Euclidean distance and 100 principal components are used. In the local normalization stage, a block of size 5×5 is used. From Fig. 2, we can see that after the processing of our algorithm, face recognition rates based on Euclidean distance method and PCA are both high. The main reason is that pose and expression of the images are very similar and our two stage de-illumination method eliminated the varying illumination effectively. From Fig. 2, we can also see that face recognition rates are highest when the number of discarded DCT coefficients is between 6 and 20. The main reason is that illumination variations cannot be eliminated thoroughly when the number is too small and much useful discriminate information is discarded incorrectly when the number is too big. From Fig. 2, we also notice that the recognition

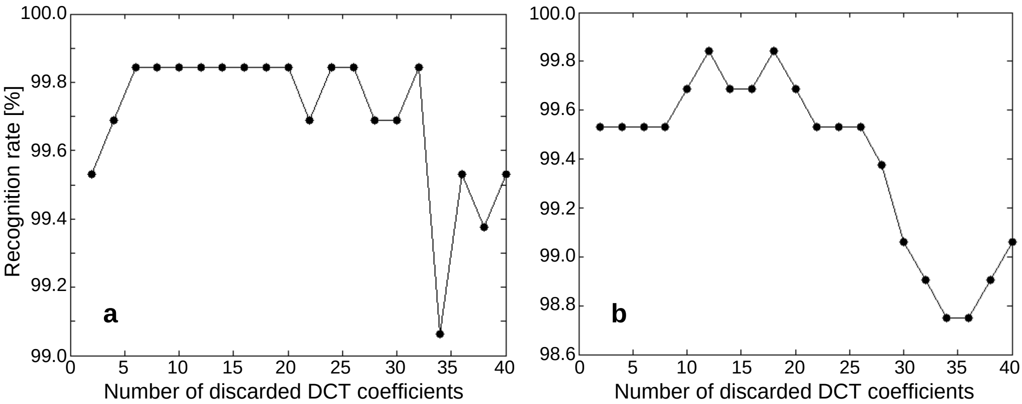

Fig. 2. Recognition performance based on different number of discarded DCT coefficients.

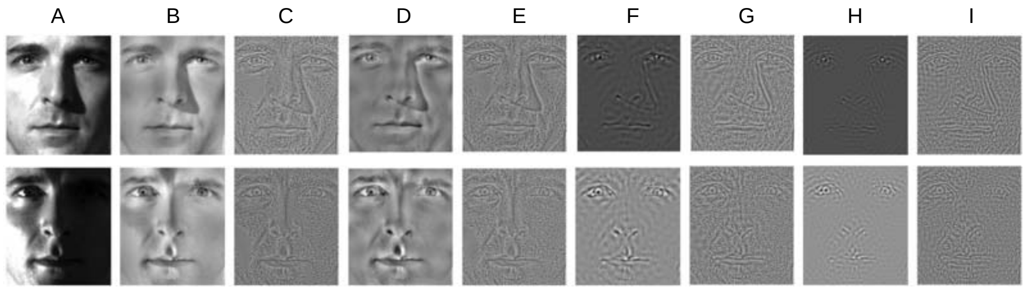

Fig. 3. Two-stage normalized results based on different number of discarded DCT coefficients.

rate drops significantly around the value of 35 only to rise again. The main reason is that when the number of discarded DCT coefficients is more than 35, some high--frequency components may be sacrificed. That is, after the local normalization stage, the processed images appear almost the same but have no effective discriminate information, which can be seen in Fig. 3 (column I). As a consequence, the recognition rate rises after the value of 35, which can be considered ineffective. The value of 12 is employed as the best number in the following experiments. With different number of discarded DCT coefficients, two images from Extended Yale B database and the normalized results after our two-stage processing are shown in Fig. 3. Column A shows the original images, columns B, D, F and H show the normalized results after the first stage when the number of discarded DCT coefficients is 6, 12, 35 and 50. Columns C, E, G and I show their corresponding normalized images after the second stage of local normalization.

3.3. Block size of local normalization

In this experiment, we use the same training samples and testing samples as in Section 3.2 to determine the best block size of local normalization stage. In the first stage, we employ 12 as the number of discarded DCT coefficients. In the second stage, we use block size of 3×3, 5×5, 7×7, 9×9, 11×11 and 13×13 in local normalization method. The recognition results with Euclidean distance method and PCA based on different block sizes are shown as Figs. 4**a** and 4**b**, respectively. In the experiment,

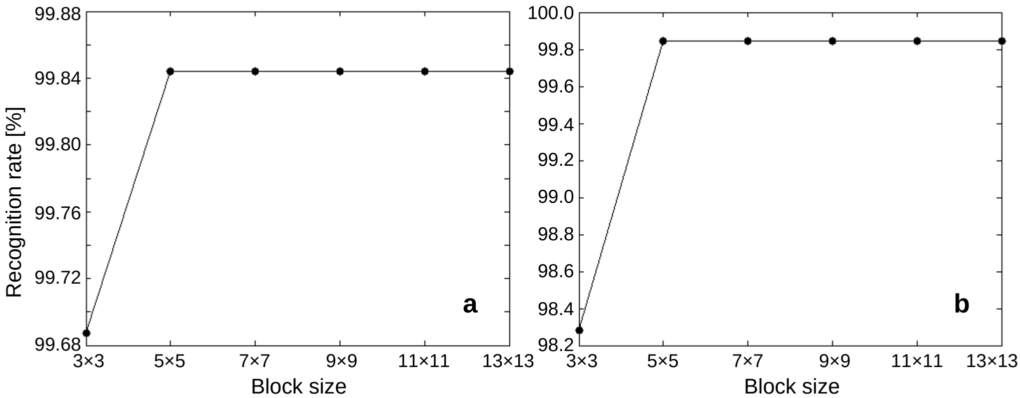

Fig. 4. Recognition performance based on different block size.

the features used with Euclidean distance are pixel values. The distance used with PCA is Euclidean distance and the number of principal components is 100. Taking recognition performance and computing complexity into consideration, we choose 5×5 as the best block size.

3.4. Comparison between zero DC and non-zero DC coefficient

We use the same training samples and testing samples as in Section 3.2 to analyze performance based on different DC coefficient. DC coefficient is set to zero and as Eq. (7), respectively, in our method to eliminate illumination variations. After the processing

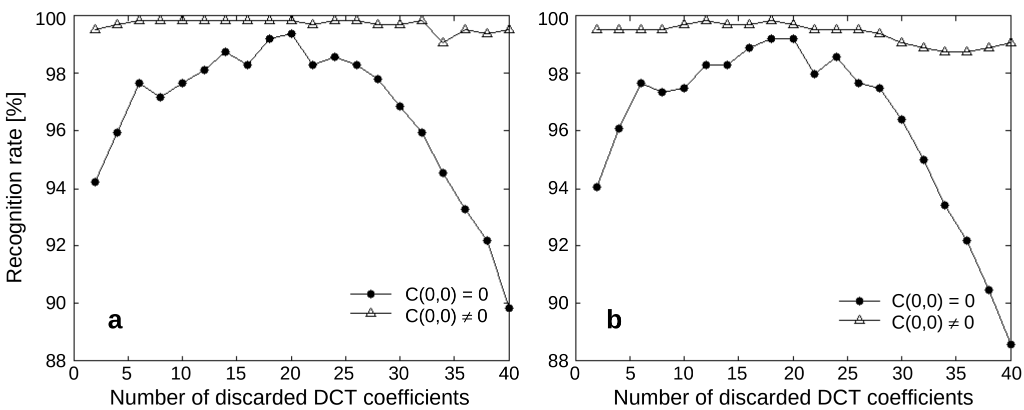

Fig. 5. Recognition results comparison between zero DC and non-zero DC coefficients.

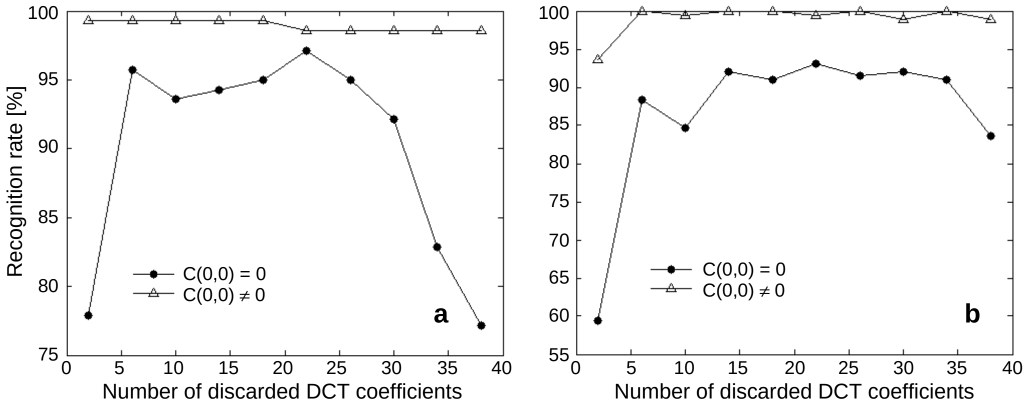

Fig. 6. Recognition results comparison between zero DC and non-zero DC coefficients on subset 4 and subset 5 of Yale B database.

of our algorithm based on the two DC coefficients, recognition performance with Euclidean distance method and PCA are shown in Fig. 5**a** and 5**b**, respectively. In this experiment, the features used with Euclidean distance are pixel values. For PCA, the distance used is Euclidean distance and 100 principal components are used.

Yale B database is used to analyze the performance based on different DC coefficient. Subset 1 of the database is used as training set. Subset 4 and subset 5 are used as testing sets. That is, the number of training images is 70 and the numbers of testing images are 140 and 190, respectively. Recognition results with Euclidean distance method on the two testing subsets based on the two different DC coefficients are shown in Figs. 6**a** and 6**b**, respectively. Here, the features used with Euclidean distance are pixel values. From Figures 5 and 6, we can see that recognition performance with DC coefficient as Eq. (7) is better than that of zero DC coefficient. The main reason is that information in DC coefficient is important and cannot be discarded at will.

3.5. Comparison between logarithm and non-logarithm images

This experiment is to evaluate whether it is necessary to reverse the image into the non-logarithm after the first de-illumination stage. Subset 1 of Yale B database is used as training set. Subset 4 and subset 5 are used as testing sets. That is, the number of training images is 70 and the numbers of testing images are 140 and 190, respectively. After the two-stage de-illumination course of our method, the error rates with logarithm images and non-logarithm images on subset 4 and subset 5 are shown as Fig. 7**a** and 7**b**, respectively. Form Figure 7, we can see that the error results with logarithm images and non-logarithm images are similar. The main reason is that the deviation caused during the non-logarithm course is compensated in the second de-illumination stage. Figure 8 shows the de-illumination results of an image in

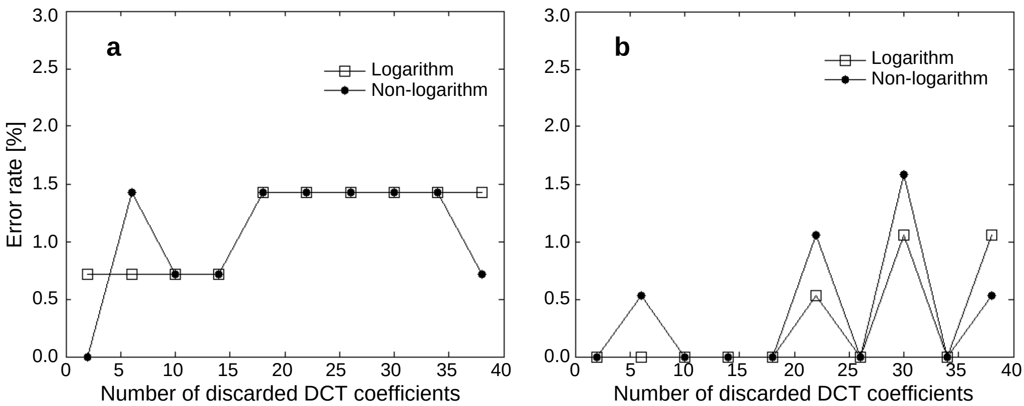

Fig. 7. Face recognition results comparison between logarithm and non-logarithm images on subset 4 and subset 5 of Yale B database.

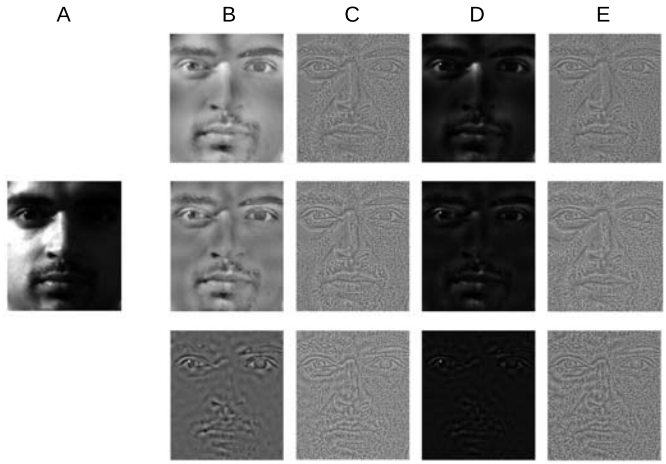

Fig. 8. Illumination normalization results comparison between logarithm and non-logarithm.

logarithm field and non-logarithm field with different number of discarded DCT coefficients. In Figure 8, column A shows the original image. Column B shows the IDCT results in the logarithm field after the first de-illumination stage with 6, 12 and 30 discarded DCT coefficients. Column C shows the corresponding results after the two de-illumination stages. Column D shows the IDCT results in the non-logarithm field after the first de-illumination stage with 6, 12 and 30 discarded DCT coefficients. Column E shows the corresponding results after the two de-illumination stages. From Figure 8, we can see that although the results in logarithm field and non-logarithm field after the first de-illumination stage are different to considerable degree, the images obtained from the second de-illumination stage are similar. This is the reason for the similarity of error rates shown in Fig. 7.

3.6. Recognition performance with different training samples

Yale B database is used to evaluate recognition performance with different training samples. We use 6 images from each subset as training samples. The rest images of this subset and the other 4 subsets are used as testing samples. After the two-stage de-illumination course of our algorithm, the error rates based on Euclidean distance method with different training sets and testing sets are shown in Tab. 1. Here, the features used with Euclidean distance are pixel values. From Table 1, we can see that the recognition performance depends on different training sets to some degree.

T a b l e 1. Error rates based on different training samples and testing samples.

		Testing sets					
		Subset 1	Subset 2	Subset 3	Subset 4	Subset 5	All
		Error rate [%]					
Training sets	Subset 1	0	0	0	1.43	0.53	0.52
	Subset 2	0	0	0	0.71	1.05	0.52
	Subset 3	0	0	0	0.71	1.05	0.52
	Subset 4	0	0	0	2.5	0.53	0.52
	Subset 5	4.29	10	5	1.43	0	3.97

3.7. Recognition performance with a single training sample

Yale B database is used to evaluate recognition performance with a single training sample. The first image of each subject from Yale B database is chosen to constitute 10 reference images. Images of the 5 subsets are matched by the 10 reference images. The error matching rates on each subset after de-illumination course of our method are shown in Tab. 2. This is suitable for the conditions when there is only one training sample.

3.8. Comparison of different de-illumination methods

Yale B database is used to compare our proposed method with the methods in other references. Subset 1 of Yale B database is used as a training set. Subset 3, subset 4 and subset 5 are used as testing sets in this experiment. The error rates based on different methods are shown in Tab. 3. From Table 3, we can see that the error rates on subset 4 and subset 5 with our method are 1.43% and 0.53%, respectively, which are lower than

T a b l e 2. Face recognition results based on a single training image.

	Subset 1	Subset 2	Subset 3	Subset 4	Subset 5
Error matching rate [%]	0.00	0.00	0.00	4.29	2.63

T a b l e 3. Recognition performance comparisons of different methods.

Methods	Error rate [%]		
	Subset 3	Subset 4	Subset 5
No de-illumination	10.8	51.4	77.4
Histogram equalization	9.2	54.2	41.1
Local normalization	0	12.14	14.74
Linear subspace [12]	0	15.0	–
Cones-attached [12]	0	8.6	–
Harmonic images [26]	0.3	3.1	–
Illumination ratio images [2]	3.3	18.6	–
Quotient illumination relighting [18]	0	9.4	17.5
9PL [27]	0	2.8	–
Our method	0	1.43	0.53

those of other methods. The recognition performance on subset 5 is superior to that on subset 4, which shows that our method is robust to slanting and large illumination variations.

4. Conclusions

A two-stage de-illumination method is proposed to deal with face images with illumination variations. In the first stage, the setting of DC coefficient and discarding some AC coefficients can eliminate illumination variations in large areas. In the second stage, local normalization method can eliminate illumination variations in small areas. Yale B and Extended Yale B databases are used in the experiments to determine the number of discarded coefficients, block size, DC coefficient, logarithm field and non-logarithm field. Our method is compared to other methods. With our method, the error rates on subset 4 and subset 5 of Yale B database are 1.43% and 0.53%, respectively, which are lower than those of other methods. The recognition performance on subset 5 is superior to that on subset 4, which shows that our method is robust to slanting and large illumination variations.

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