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Visual illumination compensation for face images using light mapping matrix

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Abstract: Illumination variation is a challenging issue in face recognition. In many conventional approaches the low-frequency coefficients are usually discarded in order to compensate the illumination variations, and hence degrade the visual quality. To deal with these problems, an adaptive normalisation-based method is proposed in this study. Each image is normalised according to its lighting attribute by mapping the low-frequency components to the normal condition instead of discarding them by applying a novel statistical concept called light mapping matrix. The method preserves the low-frequency facial features, maximising the intra-individual correlation and improves the visual quality of face images in different lighting conditions.

1 Introduction

Illumination normalisation is one of the traditional approaches used to eliminate the effects of unfavourable lighting conditions, which normalises the face image before recognition. Many approaches are proposed to perform illumination normalisation in the past couple of decades. Conventional algorithms such as histogram equalisation [1, 2], logarithmic transformation [2–4] and contrast modification [5–7] are widely used in computer vision and image processing for image enhancement. Jobson *et al.* [8] propose single-scale retinex (SSR) approach based on reflectance-illumination model which enhances image by improving the local contrast. Chen *et al.* [9] introduce logarithmic total variation model with the aim of estimating the large-scale illumination components of a face image and remove them to get the final normalised components. A different method of normalising small-and large-scale (S&L) features of a face image is proposed in [10]. Accordingly, the illumination normalisation is mainly performed on the large-scale features. In another study, a lighting aware preprocessing (LAP) is presented in [11] that estimate the lighting attributes of a face image by using spherical harmonic model, and then performs an adaptive preprocessing according to lighting attributes. Ezoji and Faez [12] present an approach for illumination-invariant face recognition based on matrix polar decomposition. In addition, several morphological methods [13, 14], which divides the isolated regions by a threshold, are proposed for extracting the shadow regions and eliminating them.

Chen *et al.* [9] introduce an approach which initially discards the low-frequency coefficients to compensate the illumination variations, since the illumination variations mainly lie in the low-frequency band. Based on this fact, various methods on discarding low-frequency coefficients in various transformed domains are proposed. Vishwakarma *et al.* [15] proposed the rescaling low-frequency DCT coefficients to lower values. Perez and Castillo [16] propose a similar method which applies Genetic Algorithms to search appropriate weights to rescale the low-frequency DCT coefficients as well. Furthermore, Nie *et al.* [17] and Zhichao and Joo [18] propose discarding coefficients, respectively, in discrete wavelet transform (DWT) and block-wise Walsh–Hadamard transform (WHT) instead of DCT to eliminate the negative effects of illumination variations. Preda and Vizireanu [19] use the wavelet coefficients in luminance component for watermark embedding. In all the above-mentioned methods, the fixed elements in frequency domain are discarded or changed with the same scale in order to compensate illumination variations, whereas Dabbaghchian *et al.* [20] claimed that the discrimination power of all the coefficients is not the same, and some of them are more discriminant than others. Dabbaghchian *et al.* [20] proposed a statistical approach to select discriminant features which have small variation within a class, and large variation between the classes.

On the other hand, most of the conventional approaches preprocess all the face images in the same way without considering the specific lighting in each face image. However, in most cases the low-frequency coefficients are discarded in order to compensate the illumination variations. In this paper, we focus on developing a novel method to adjust each of the low-frequency components separately depending on the lighting conditions in image. Accordingly, the proposed method preserves the low-frequency features of the face and not only improves the performance of face recognition, but also increases the correlation between the images of an individual in different lighting conditions. The main objectives of this paper are as follows:

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1. Adaptive preprocessing for each testing image based on its lighting condition.
2. Preserving and adjusting the low-frequency facial features instead of discarding them.
3. Improving visual quality of reconstructed images.

In this paper, a light mapping matrix (LMM) is introduced for adaptive illumination compensation. The rest of the paper is organised as follows: Section 2 describes the illumination compensation approach in detail. Experimental results and discussions are presented in Section 3. Finally, the conclusion is given in Section 4.

2 Illumination normalisation in logarithm discrete cosine transform (DCT) domain

2.1 Feature extraction

Logarithm transform is used in image enhancement to expand the values of dark pixels [1, 3]. Hence, as shown in [9], illumination compensation can be implemented in the logarithm domain.

On the other hand, it is found that the illumination variations mainly lie in the low-frequency components of a face image [9]. DCT is a powerful transform in image processing applications, including face recognition [15, 20], which is used to convert the spatial domain of an image into the frequency one. The two-dimensional (2D) $M \times N$ DCT for original image $\boldsymbol{f}(x, y)$ is defined as follows

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

where

$$\alpha(u) = \begin{cases} 1/\sqrt{M}, & u = 0 \\ \sqrt{2/M}, & 1 \le u \le M-1 \end{cases}$$
$$\alpha(v) = \begin{cases} 1/\sqrt{N}, & v = 0 \\ \sqrt{2/N}, & 1 \le v \le N-1 \end{cases} \tag{2}$$

In the proposed approach, the DCT is used to obtain the frequency components of the face image in logarithm domain. The way of selecting DCT coefficients is shown in Fig. 1. D_{dis} represents the number of first row of DCT coefficients that is used to illumination compensation; its default is 20.

Discarding the low-frequency of DCT coefficients in the logarithm domain is in expense of losing some vital low-frequency facial features. The proposed illumination compensation method normalises the low-frequency components instead of discarding them.

2.2 Basis of LMM

In normal lighting conditions, variation of low-frequency coefficients for an individual face image is very small and ignorable. So the variance of low-frequency DCT coefficients of specific individuals under normal lighting conditions in successive iteration is almost the same. Empirical study shows that by increasing the angle of lighting for the same individuals the variance increases significantly.

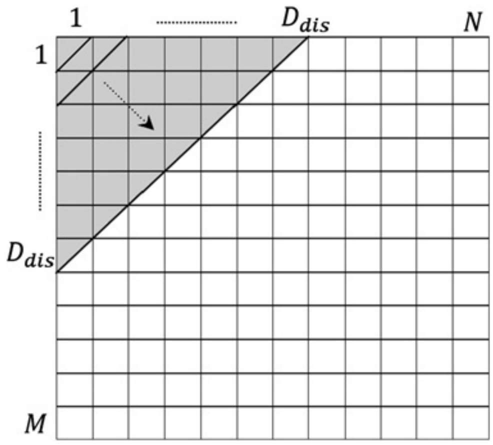

Fig. 1 *Way of selecting DCT coefficients*

To estimate the LMM, the ratio of coefficient variation in each lighting-class to its normal lighting-class (first lighting-class) is used. The following steps describe creating LMM.

First, various images from lighting-classes are randomly selected as training images. Then, the frequency matrix '$\boldsymbol{A}$' is generated, for all training images by applying 2D-DCT transform on logarithmic images.

Furthermore, the average of all training frequency matrices in normal lighting-class (class 1) is found as follows

$$\boldsymbol{M}_{ij}^{1} = \frac{1}{S_1}\sum_{s=1}^{S_1}\boldsymbol{A}_{ij}^{1}(s) \tag{3}$$

where $\boldsymbol{A}^c$ indicate the DCT transform matrix of the input image of lighting-class c; and S_c is the number of training images in lighting-class c.

Afterward, the variance of each coefficient to the normal lighting is computed for each class

$$\boldsymbol{V}_{ij}^{c} = \frac{1}{S_c}\sum_{s=1}^{S_c}\left(\boldsymbol{A}_{ij}^{c}(s) - \boldsymbol{M}_{ij}^{1}\right)^2, \quad c = 1, 2, \ldots, 5 \tag{4}$$

Finally, the LMM for each lighting-class is estimated as follows

$$\text{LMM}_{ij}^{c} = \left(\boldsymbol{V}_{ij}^{c} / \boldsymbol{V}_{ij}^{1}\right)^{1/2}, \quad c = 2, \ldots, 5 \tag{5}$$

where c indicates as the lighting-class number.

Light mapping, would be performed on the coefficients whose variance is more than that of the normal class. Hence, the matrix elements of the LMM with smaller amounts of one are replaced with 'one'

$$\text{LMM}_{ij} = \begin{cases} 1, & \text{LMM}_{ij} < 1 \\ \text{LMM}_{ij}, & \text{LMM}_{ij} \ge 1 \end{cases} \tag{6}$$

Fig. 2 shows the obtained LMM elements of four lighting-classes of completed Yale B image data set. Only the first 25×25 elements which correspond to the low-frequency DCT coefficients are shown for

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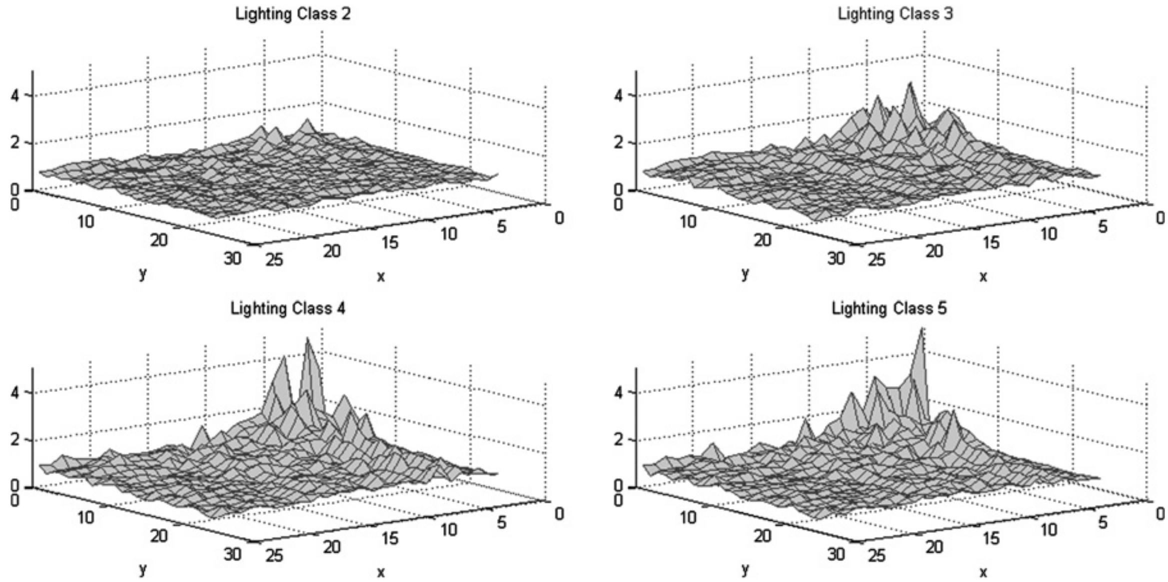

Fig. 2 *LMMs in different lighting-classes*

lighting-classes 2–5. The LMM elements for the normal lighting-class are equal to 'one'.

2.3 Proposed illumination compensation method

The overview of the proposed adaptive light mapping (ALM) method is shown in Fig. 3. The method consists of two stages. In the first stage, the lighting-class of the input image is estimated based on the low-frequency components. Then, in the second stage, LMMs will be applied on images with unknown lighting conditions for illumination compensation. The detail of each stage is explained in the following sections.

2.3.1 Lighting-class estimation: Since illumination variations mainly lie in low-frequency components, the lighting-class of a face can be estimated by these coefficients. So we use the first DCT coefficients with $D_{\text{dis}} = 20$ to learn the lighting-classes of face images.

LS-TSVM is considerably fast and successful variant of twin SVM, which perform the classification by using two non-parallel hyperplanes unlike conventional SVMs which utilise a single hyperplane [21]. Recent and on growing research [21, 22] shows that LS-TSVM is very powerful and reaches better accuracy rate in classification application with less time complexity. It only needs to compute two linear equations instead of solving the quadratic programming problems (QPPs).

In this paper, we have a multi-class LS-TSVM classification. Therefore the binary LS-TSVM classifier is applied on each pair of classes. In this case, we would have $N(N-1)/2$ pairs of non-parallel hyperplanes (which N is the number of classes), and the lighting-class is determined by voting of binary classifiers.

2.3.2 Adaptive illumination compensation: After estimating the lighting-class of images, the corresponding LMM is used to compensate the undesirable lighting effects of the face image.

Suppose that '$\boldsymbol{I}^{\text{Probe}}$' is a probe image with an unknown lighting condition, then the matrix '$\boldsymbol{A}^{\text{Probe}}$' is defined as 2D-DCT transform of '$\boldsymbol{I}^{\text{Probe}}$' in logarithm domain.

Accordingly, the lighting-class of the probe image is determined by applying LS-TSVM on low-frequency

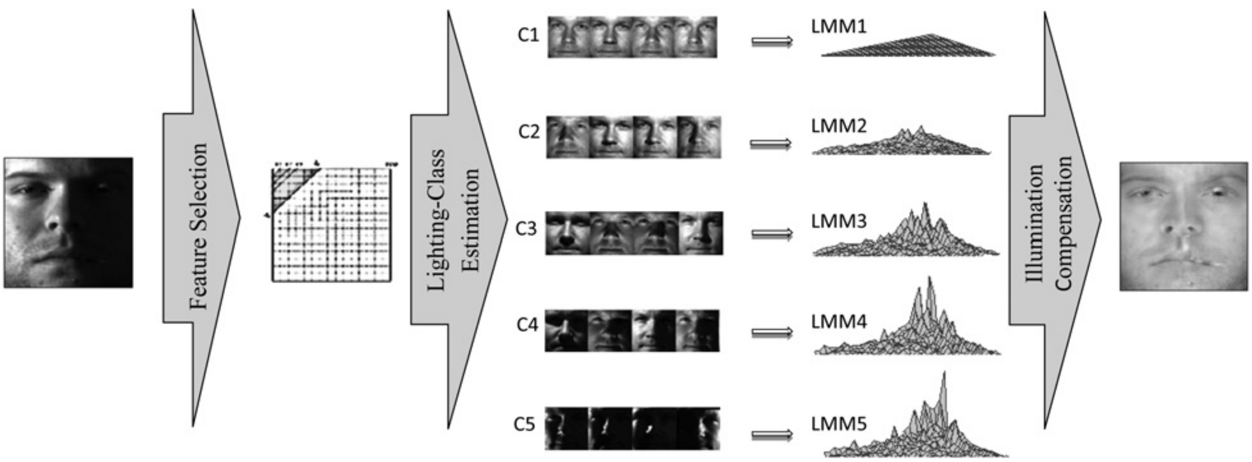

Fig. 3 *Block diagram of the proposed ALM approach*

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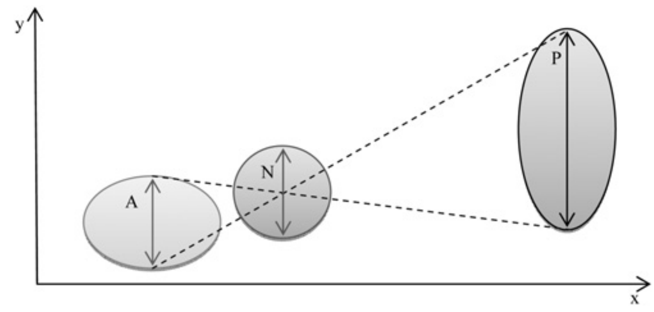

Fig. 4 *Light mapping for a hypothetical class P*

A: normal lighting-class and N: adaptive light mapping of class P

components of 'A^{Probe}'

$$c = \text{TSVM}\left(A_{ij}^{\text{Probe}}\right) \tag{7}$$

Then, the illumination compensation is performed by adjusting the low-frequency component of DCT as follows

$$A_{ij}^{\text{Normal}} = \frac{A_{ij}^{\text{Probe}} - M_{ij}^{1}}{\text{LMM}_{ij}^{c}} + M_{ij}^{1} \tag{8}$$

Fig. 4 shows an example of light mapping for hypothetical class *P*. Assuming that the class *A* is the normal lighting-class, class *N* shows the result of illumination compensation for class *P*, Which is calculated by (8).

Table 1 Result of classification of lighting-classes by different learning methods.

Methods	Lighting-class/(no. of images)				
	5/ (714)	4/ (526)	3/ (455)	2/ (456)	1/ (263)
Naïve Bayes [24]	91 .47	82 .12	78 .48	73 .51	67 .11
SVM [24]	94 .70	88 .44	84 .61	78 .99	65 .15
LS-TSVM (c_1, c_2 = 0.075)	95.85	89.21	87.56	92.04	94.07

3 Experiment results

3.1 Databases

Yale B [23] and extended Yale B [8] are two popular databases used for the evaluation in this study. In Yale B Face database, there are 64 different illumination conditions for ten persons in nine different poses. The images are divided into five subsets based on the angle between the lighting direction and the camera axis. The extended Yale B database consist 16 128 images of 28 persons with the same condition as Yale B.

In our experiments, only 64 frontal images of per person under different illumination conditions are considered. After combining the extended Yale B with the Yale B, there are 2414 images of 38 subjects named as the completed Yale B. The images are divided into five subsets according to the light source directions and the camera axes (that are 0–12°, 13– 25°, 26– 50°, 51–77°, >77°). The cropped and aligned images provided by Chen *et al.* [9] are directly used. Here, the size of each image is 192 × 168. Images of subset 1 are used as the gallery, and the rest of images as probes.

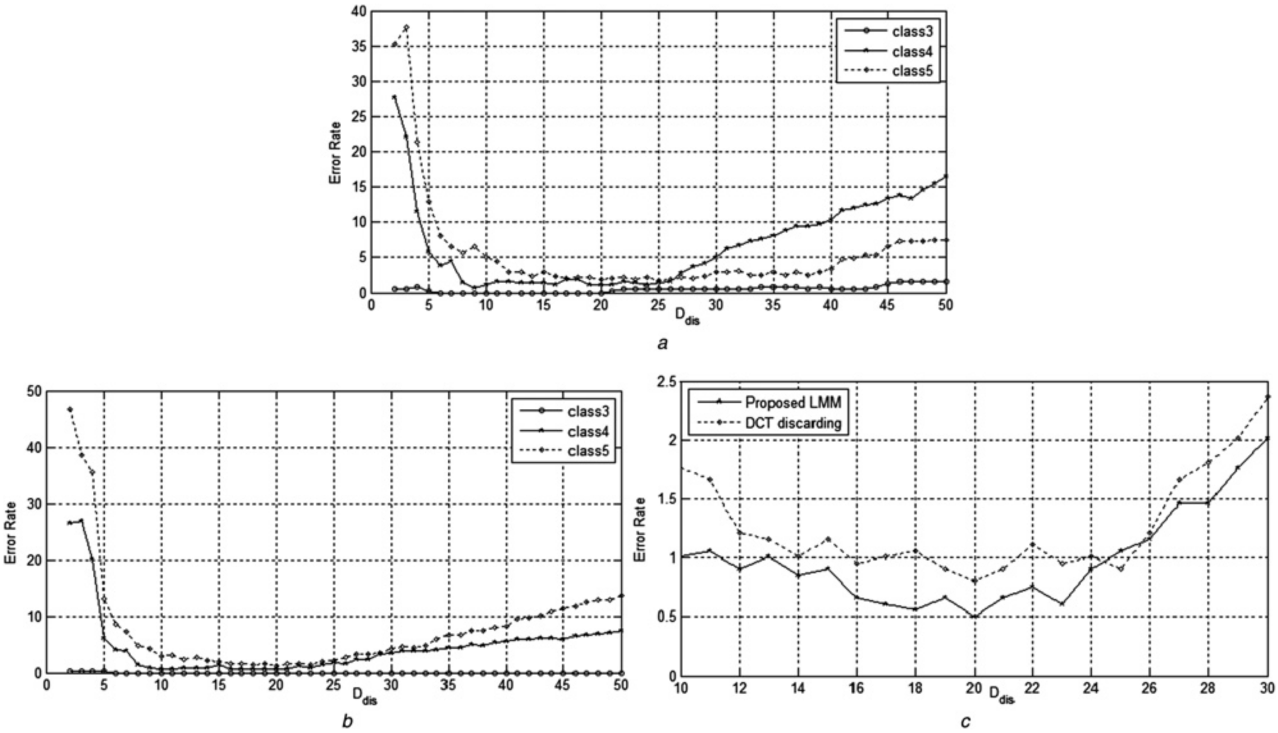

Fig. 5 *Error rate on the completed Yale B database with different D_{dis}*

a DCT discarding
b Adjusting coefficient with proposed LMM
c Compare overall results of Figs. 5a and b

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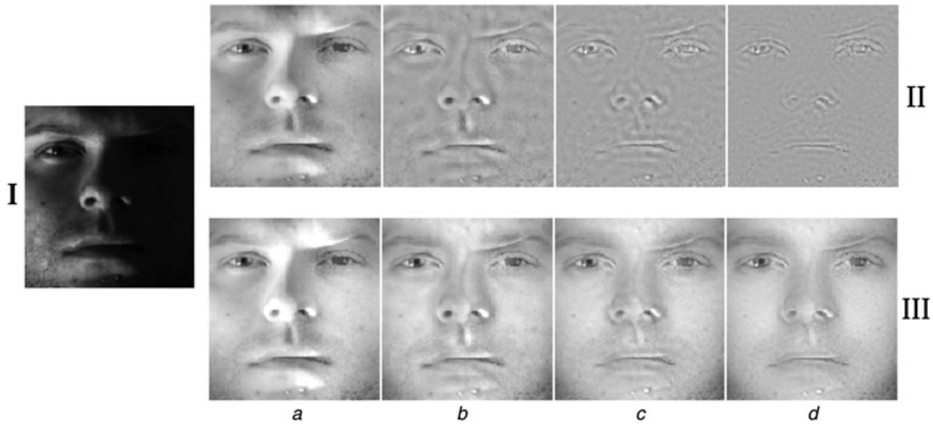

Fig. 6 *Reconstructed images with different D_{dis}*

a $D_{\text{dis}} = 5$
b $D_{\text{dis}} = 20$
c $D_{\text{dis}} = 35$
d $D_{\text{dis}} = 50$
(I) original image; (II) DCT discarding; and (III) proposed approach

Standard correlation coefficient between the probe and the gallery images is used for recognition phase. In the proposed method because of the extreme illumination variations of lighting-classes 4 and 5, the adjusted coefficients in these classes are used with a weight of 0.4 to calculate the correlation.

3.2 Lighting-class estimation

As previously mentioned, the first DCT coefficients (with $D_{\text{dis}} = 20$) are used in LS-TSVM to learn and then to estimate the lighting-classes. To evaluate the performance of LS-TSVM, ten-fold cross validation method is used. The accuracy of LS-TSVM method in completed Yale B is compared with Naïve Bayes and SVM [24], which are two powerful methods for classification, in Table 1. *F*-measure (the harmonic mean of precision and recall) is used to evaluate the accuracy

$$F = 2\,\frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{9}$$

The results show the efficiency of LS-TSVM in lighting-class estimation in comparison to other classification methods. This is because of the ability of LS-TSVM to classify cross data set (by using two non-parallel hyperplanes) over other classifiers.

Equation (10) shows the confusion matrix for LS-TSVM classifier. As it is seen, the most errors occurred are between the adjacent classes. However, it is inevitable because of the vicinity of lighting angels in adjacent classes and would not have much effect on the results of illumination compensation

$$\boldsymbol{C} = \begin{bmatrix} 251 & 11 & 1 & 0 & 0 \\ 8 & 440 & 8 & 0 & 0 \\ 11 & 41 & 380 & 23 & 0 \\ 1 & 7 & 24 & 468 & 28 \\ 0 & 1 & 0 & 32 & 681 \end{bmatrix} \tag{10}$$

Table 2 Comparison between different illumination compensation methods

Method	Subset			
	5	4	3	2
raw images	4.3	12.5	20.8	87.4
Hist.equal. (HE)	9.6	15.1	32.2	89.5
log correlation	7.8	16.7	57.4	86
LTV [25]	78.3	76.1	79.4	99.8
RLS log-DCT [26]	84.4	87.6	87.1	100
ARHE + EdgeE [27]	80.5	90.4	84.4	100
SSR [8]	77.3	78.7	99.1	100
S&L(NPL-QI) [10]	69.1	87.0	96.7	100
PP + LTP/DT [28]	97.2	99.2	100	100
DCT discarding ($D_{\text{dis}} = 20$)	98.1	98.8	100	100
proposed LMM ($D_{\text{dis}} = 20$)	98.8	99.3	100	100

Table 3 Results of the proposed illumination compensation based on lighting-class estimation

Method	Subset			
	5	4	3	2
Naïve Bayes + LMM	89.7	91.3	91.4	99.3
SVM + LMM	87.7	93.7	95.3	84.1
LS–TSVM + LMM	97.8	98.6	98.3	99.2

3.3 Adjusting DCT coefficients against discarding them

Illumination variations and facial features are not separable in frequency domain. Some illumination variations, especially shadows and specularities, like some facial features lie in the same frequency bands.

In most of the existing methods, for compensating these variations, by discarding low frequency, some facial information is also discarded [9].

Fig. 5*a* shows the error rate of discarding method, simulation based on Chen's approach in each lighting-classes for different values of D_{dis}. Although, Chen *et al.* [9] showed that high performance can be still obtained without these features, but with increasing

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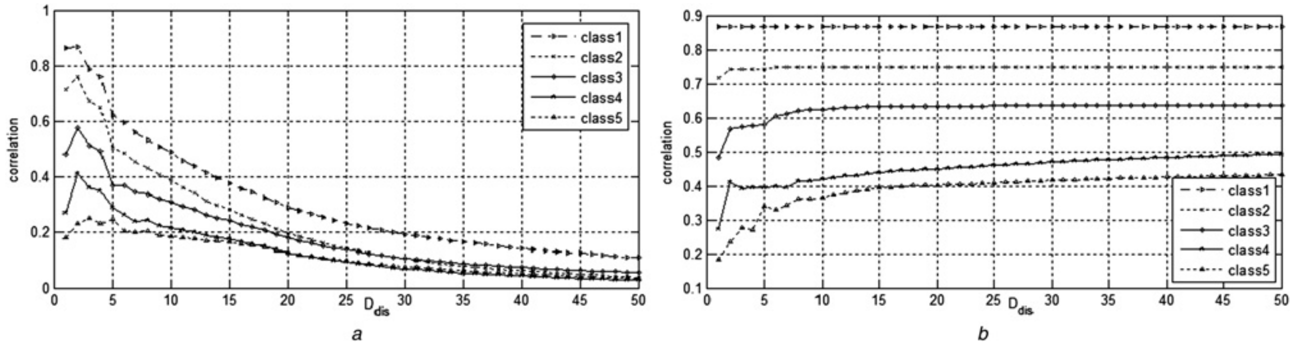

Fig. 7 *Intra-individual correlation in different D_{dis} by*

a DCT discarding
b Adjusting coefficients with the proposed LMM

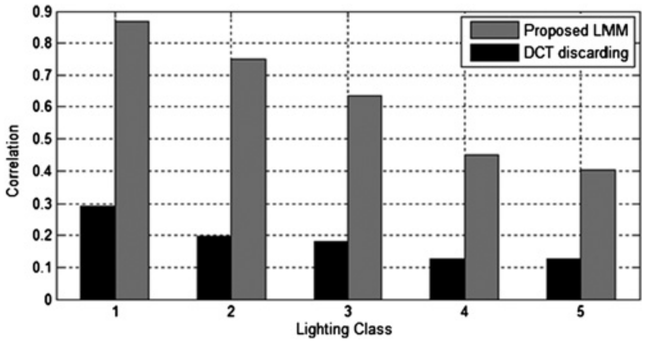

Fig. 8 *Comparing overall intra-individual correlation in different method in D_{dis} = 20*

database size, the performance decreases. This is because of limiting of features.

In the proposed method, the low-frequency facial features are adjusted by mapping each feature to that of normal lighting condition. In this way, it is possible to correctly preserve the facial features as much as possible.

The error rate of the proposed method is calculated in each lighting-class for different values of D_{dis} as shown in Fig. 5*b* . Fig. 5*c* provides the results of simulated Chen's method and the proposed approach on completed Yale B. As it is found, both methods obtained their best results in $D_{\text{dis}} = 20$.

In Fig. 6, the reconstructed images obtained by DCT discarding and the proposed method are shown for different value of D_{dis}. The results show that the proposed method is able to preserve the more facial features in frequency domain.

Table 2 shows the results of some interesting approaches in illumination compensation on completed Yale B. The last row

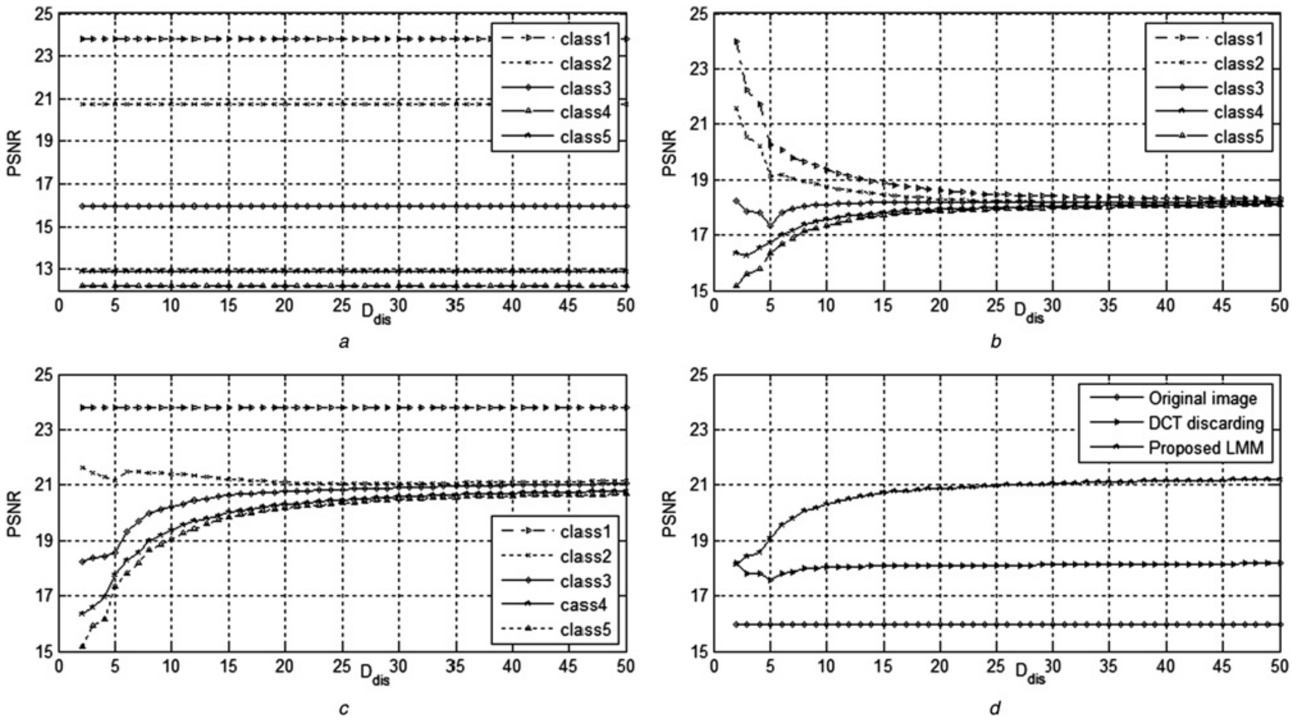

Fig. 9 *Average PSNR with respect to the original images in different D_{dis}*

a Raw images
b DCT discarding
c Adjusting coefficients with the proposed LMM
d Compare overall PSNR for Figs. 9a–c

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of Table 2 shows the face recognition rate obtained by the proposed method. As it is found, the best results are obtained by the proposed method for predefined lighting-classes.

Table 3 shows the results of the proposed method when the lighting-class estimation is found by some learning methods. As it is seen, the classification error (as is shown in Table 1) has affected on recognition rate in different subsets.The results show the superiority of LS–TSVM + LMM in illumination compensation based on lighting-class estimation.

3.4 Maximising intra-individual correlation

Ignoring the low-frequency facial features in illumination invariant feature extraction methods, lead to decreasing the correlation between the original gallery and the reconstructed images of an individual as shown in Fig. 6*a* . These methods also discard the low-frequency component from gallery images applicable in identification.

One of the advantages of the proposed method is that, the intra-individual correlation with the gallery images is properly preserved in varying illumination; consequently, there is no need to apply changes on the gallery images to identify faces.

Fig. 7 shows the average correlation between the original gallery images of each individual and the reconstructed image of the same individual in different lighting-classes, obtained by discarding method and proposed method for different value of D_{dis}.

As it can be found, the correlation coefficient is decreased by increasing D_{dis} in discarding method as shown in Fig. 7*a*. On the other hand, this is incremental in the proposed method as shown in Fig. 7*b*. Furthermore, it is converged to a constant value for each lighting-class. In this regard, the proposed method is also appropriate for face verification under varying illumination, as it proposes the proper threshold for each lighting-class. The average correlation obtained by both methods in $D_{dis} = 20$ is compared in Fig. 8. As we can see in Figs. 7 and 8, the significant improvement compared to discarding method would be achieved.

3.5 Image quality evaluation

In this section, the quality of the reconstructed images is evaluated by using the peak signal-to-noise ratio (PSNR) which is one of the various objective evaluation algorithms for measuring image quality [29] .

Fig. 9 shows the average PSNR results in different lighting-classes (with the exception of self-image comparison in class 1). The higher PSNR represents the closer similarity between reconstructed images and gallery.

As it can be seen, the proposed method has achieved the better image quality (PSNR) in different lighting-classes. Table 4 shows the average PSNR for different methods.

Table 4 PSNR results of reconstructed images by $D_{dis} = 20$

Methods	Lighting class					
	1	2	3	4	5	Overall
original images	23.81	20.71	15.95	12.22	12.86	15.97
DCT discarding	18.60	18.29	18.17	17.93	17.85	18.09
proposed LMM	23.81	21.09	20.76	20.28	20.16	20.88

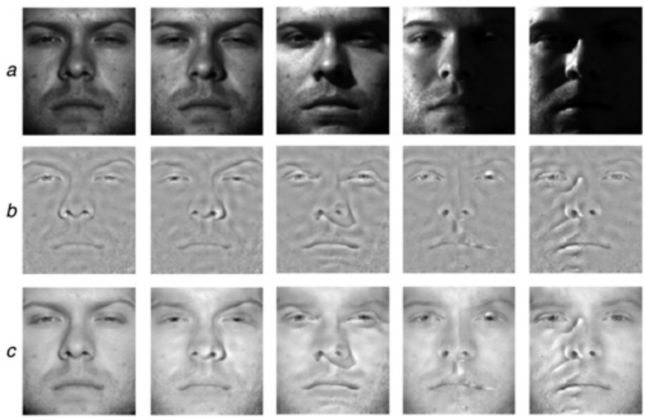

Fig. 10 *Normalised images with $D_{dis} = 20$*

a Original image
b DCT discarding
c Proposed method

The proposed method represents an average PSNR growth of 2.79 dB in comparison to discarding method.

In Fig. 10, the images of a person in different lighting-classes are shown. The second and the third rows show the reconstructed images by DCT discarding (Chen method) and the proposed method, respectively . As it shows, the clarity and the appearance of reconstructed images are considerably improved in proposed approach.

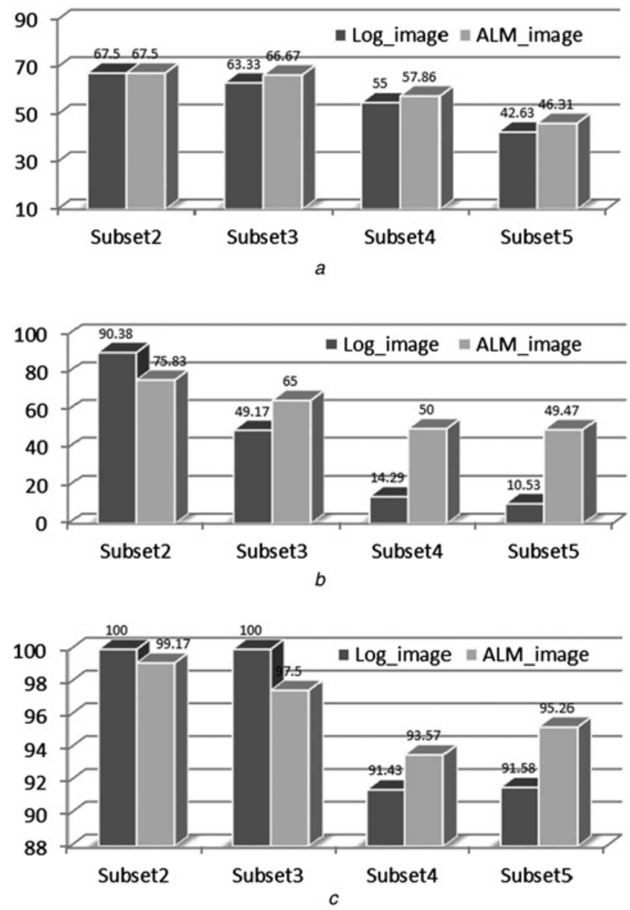

Fig. 11 *Face recognition rate by*

a SVM
b Naïve–Bayes
c LDA in different lighting conditions

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3.6 Face recognition by different classifiers

As we can see from the experiments; the illumination compensation method introduced in this paper can improve the visual quality of face images, therefore it can be used as one of the pre-processing of face images to improve the face recognition results.

In this section we use several classifiers for face recognition based on ALM. We evaluate their performance on Yale B face database during two experiments.

First experiment : In this experiment, the seven images of each person in normal lighting conditions (subset 1) are applied to train the classifiers and the other images are used for test.

We use of SVM, Naïve-Bayes and LDA for face recognition in different illumination and calculate the recognition rate based on logarithmic images and the reconstructed images (by ALM) for each classifier. Fig. 11 shows the results obtained by this experiment.

As can be seen in Fig. 11 in subsets 4 and 5 (which is mostly due to the angle of lighting, shadows have more severe), using the reconstructed images leads increasing recognition rates in all classifiers. According to decrease of recognition rate in subset 2, based on Naïve-Bayes

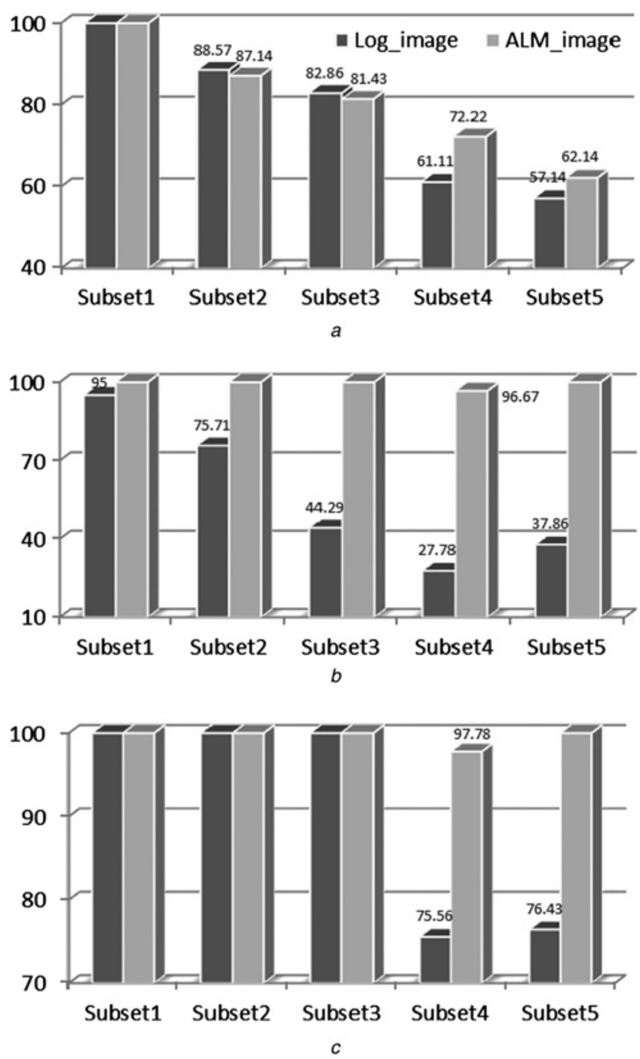

Fig. 12 *Face recognition rate*

a SVM
b Naïve–Bayes
c LDA in different lighting classes

(Fig. 11*b*) and in subsets 2 and 3 based on LDA (Fig. 11*c*) (which part of it is caused by classification error by LS-TSVM), it can be concluded that by use of the proper classifier we could ignore illumination compensation on images with low illumination changes (e.g. subsets 2 and 3).

Second experiment: In this experiment, five subsets of Yale B are considered as five independent lighting class and in each class first five images is used for training and others used for test. The recognition results obtained for each subset by different classifier is shown in Fig. 12.

As we can see, using the reconstructed images leads to improve the face recognition rates in different lighting classes for all three classifiers.

4 Conclusions

In this paper, an ALM method as a preprocessing technique for illumination compensation in logarithm DCT domain was proposed. Most of the existing methods use the same way to all the face images, and the low-frequency coefficients are usually discarded in order to compensate the illumination variations.

An adaptive normalisation for each image was applied based on its lighting attribute estimated by LS-TSVM . The low-frequency components of the image were mapped into the normal lighting condition by LMM. In this way, the low-frequency details of a face image were preserved as far as possible and visual quality (PSNR) of face images in different lighting conditions was improved.

The approach had some remarkable advantages: (i) the ability to perform preprocessing on each image based on its lighting condition, (ii) preserving the low-frequency facial features by normalisation instead of discarding them and finally (iii) improving the quality of reconstructed images. Experimental results show the efficiency of the proposed method in face recognition under different lighting conditions on Yale B and extended Yale B face databases. In our future work, we will focus on spatial shadow effects as the lighting attribute to improve the performance.

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