

Face Illumination Normalization on Large and Small Scale Features

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Abstract

It is well known that the effect of illumination is mainly on the large-scale features (low-frequency components) of a face image. In solving the illumination problem for face recognition, most (if not all) existing methods either only use extracted small-scale features while discard large-scale features, or perform normalization on the whole image. In the latter case, small-scale features may be distorted when the large-scale features are modified. In this paper, we argue that large-scale features of face image are important and contain useful information for face recognition as well as visual quality of normalized image. Moreover, this paper suggests that illumination normalization should mainly perform on large-scale features of face image rather than the whole face image. Along this line, a novel framework for face illumination normalization is proposed. In this framework, a single face image is first decomposed into large- and small- scale feature images using logarithmic total variation (LTV) model. After that, illumination normalization is performed on large-scale feature image while small-scale feature image is smoothed. Finally, a normalized face image is generated by combination of the normalized large-scale feature image and smoothed small-scale feature image. CMU PIE and (Extended) YaleB face databases with different illumination variations are used for evaluation and the experimental results show that the proposed method outperforms existing methods.

1. Introduction

Face recognition technologies have been widely applied in the areas of intelligent surveillance, identity authentication, human-computer interaction and digital amusement. However, one of the limitations in deploying the face recognition for practical use is the relatively low performance under illumination variations. It has been observed that the effect of illumination variations in face

images is more significant than the effect of the image variations due to the change in face identity [1]. Most existing methods for face recognition such as principal component analysis (PCA) [2], independent component analysis (ICA) [3] and linear discriminant analysis (LDA) [19] based methods are sensitive to illumination variations [4]. So face illumination normalization is a central problem in face recognition and face image processing, and then many well-known algorithms have been developed to tackle this problem.

For a face image, we call its small intrinsic details the small-scale features and call its large intrinsic features, illumination and shadows cast by big objects, the large-scale features. Accordingly, existing techniques for illumination normalization can be roughly divided into two categories. The first category aims at extracting the small-scale features that are conceived to be illumination invariant for face recognition. Methods in this category include logarithmic total variation (LTV) model [5], self quotient image (SQI) [6] and discrete wavelet transform (DWT) based method [7]. However, all these methods discard the large-scale features of face images, which may be useful for recognition.

The second category aims at compensating the illuminated image. Methods of this category do illumination normalization directly on the whole face image. Some representative algorithms include histogram equalization (HE) [8], shape-from-shading (SFS) [9], illumination cone [10], BHE and linear illumination model [11], low-dimensional illumination space representation [12], illumination compensation by truncating discrete cosine transform coefficients in logarithm domain [13], quotient image relighting method (QI) [14] and the non-point light quotient image relighting method (NPL-QI) based on PCA subspace [15] [16]. In particular, QI and NPL-QI can generate image simulating arbitrary illumination conditions. However, these methods also distort the small-scale features simultaneously during the normalization process. Therefore the recognition

performance will be degraded, as small-scale features are always invariant to illumination.

Since most (if not all) of existing methods focus on either the small-scale features or the whole face image, it is hard to get good recognition performance and generate normalized face image with good visual results. Instead, this paper proposes a new framework, in which large- and small- scale features of a face image are processed independently. In the proposed framework, a face image is first decomposed into a large-scale feature image and a small-scale feature image. Normalization is then mainly performed on the large-scale feature image, and meanwhile a smooth operator is applied on the small-scale feature image. Finally, the processed large- and small- scale feature images are combined to generate a normalized face image.

The rest of this paper is organized as follows. In section 2, the proposed framework is presented. In section 3, experimental results are reported. Finally, conclusion of this paper is given in section 4.

2. Proposed Framework

2.1. Motivation & Algorithm Overview

Based on the Lambertian model, a face image I can be described by

$$I = rn^T \bullet l = R \otimes L, \quad (1)$$

where r is the albedo of face, n is the surface normal of face, \bullet is the dot product, l is the illumination and \otimes is the pointwise product. Denote R as the reflectance image and L as the illumination image. As R depends only on the albedo and surface normal, so it is the intrinsic representation of an object. Many existing methods attempt to extract the reflectance image for face recognition. Unfortunately, estimating R from I is an ill-posed problem [17]. To solve this problem, Chen *et al.* proposed a practical methodology [5]. Denote R_l as the albedo of large scale skin areas and background. Then, based on Eq.(1) the following result is obtained:

$$\begin{aligned} I(x, y) &= R(x, y)L(x, y) \\ &= (R(x, y) / R_l(x, y))(R_l(x, y)L(x, y)) \\ &= \rho(x, y)S(x, y) \end{aligned} \quad (2)$$

In this case, the term $\rho = R(x, y) / R_l(x, y)$ contains only the smaller intrinsic structure of a face image, and S contains not only the extrinsic illumination and shadows casted by bigger objects but also the large intrinsic facial structure. In this paper, ρ is called the small-scale feature image and S is called the large-scale feature image.

As we know, illumination variation mainly affects the large-scale features of a face image and it is important to retain the invariant features such as the small-scale features during illumination normalization. We observe from Eq.(2) that an image could be decomposed into a small-scale

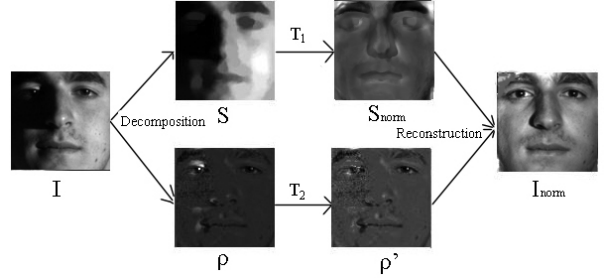


Figure 1: Diagram of the proposed framework

feature image and a large-scale feature image. This implies that illumination normalization could be performed on S meanwhile the small intrinsic facial features in ρ could keep unchanged. Even some necessary processing is performed on ρ , it would be independent to the one on S . Moreover, after normalizing S and ρ , the normalized face image can also be generated by Eq. (2). Motivated by this observation, this paper proposes a new framework for illumination normalization described as follows:

$$\begin{aligned} I_{norm}(x, y) &= \rho'(x, y)S_{norm}(x, y) \\ s.t. \begin{cases} I(x, y) = \rho(x, y)S(x, y) \\ \rho' = T_2(\rho) \\ S_{norm} = T_1(S) \end{cases} \end{aligned} \quad (3)$$

Fig. 1 shows the diagram of the proposed framework. It consists of four steps, namely face image decomposition, smoothing on small-scale feature image (T_2), illumination normalization on large-scale feature image (T_1) and reconstruction of normalized images. Details of each step are discussed as follows.

2.2. Face Image Decomposition Using Logarithmic Total Variation

First, we decompose a face image into a small-scale feature image and a large-scale feature image as shown in Eq.(2). In this paper, we employ a recently developed LTV model [5] for image decomposition. Compared to existing methods, LTV has the capabilities of edge-preserving and multi-scale decomposition. By performing logarithm transform on Eq.(2), LTV model is described as follow:

$$\begin{aligned} f(x, y) &= \log I(x, y) = \log \rho(x, y) + \log S(x, y) \\ u^* &= \arg \min_u \{ \int |\nabla u| + \lambda \|f - u\|_L \} \\ v^* &= f - u^* \end{aligned} \quad (4)$$

where $\int |\nabla u|$ is the total variation of u and λ is a scalar threshold on scale. In our experiments, we set $\lambda = 0.4$. In Eq.(4), minimizing $\int |\nabla u|$ would make the level sets of u have simple boundaries, and minimizing $\|f - u\|_L$ would ensure the approximation of u to f . PDE-based gradient descent technique, interior-point second-order cone program (SCCP) algorithm, or network flow method can be

used for solving Eq.(4). In this paper, SCCP is used, and therefore, ρ and S can be approximately estimated by solving Eq.(4) as follows:

$$S \approx \exp(u^*), \quad \rho \approx \exp(v^*) \quad (5)$$

An example of the face image decomposition result is showed in Fig. 2.

In [5], Chen et al. only directly use small-scale feature image for face recognition, while the large-scale feature image is not taken into consideration. Moreover, no normalization is further performed on large- and small-scale feature images in [5] for generating face image under normal illumination.

2.3. Smoothing on Small-Scale Feature Image

As shown in Fig. 2, after face image decomposition using LTV, some light spots may appear in the small-scale feature image ρ under some challenging illumination condition, which also appear in the illustration [5]. Although the influence of these spots might be ignored for face recognition, it would have negative effect on the visual quality of the reconstructed image at the final step in the proposed framework. For this reason, a threshold minimum filtering is performed on ρ for getting better visual results later.

Suppose (x_0, y_0) is the center point of convolution region. Then, the threshold minimum filtering performs as follows. The filter kernel will convolute only if $\rho(x_0, y_0) \geq \theta$, where θ is an empirical threshold. In our experiment, a 3×3 mask is used and each image is convolved twice. An example of the filtering result is illustrated in Fig. 3.

2.4. Illumination Normalization on Large-Scale Feature Image

Recall the discussion of Eq.(2). Although the extrinsic illumination and shadows cast by bigger objects appear in the large-scale feature image, S may contain the larger intrinsic facial structures that are also illumination invariant. In order to improve the visual quality of normalized face image, large-scale features have to be used. For these reasons, the large-scale feature image should be normalized. To remove the illumination effect in S , some effective illumination normalization processing is needed. In this paper, two methods, namely NPL-QI and truncating DCT coefficients in logarithm domain (LOG-DCT) are separately employed for this purpose. NPL-QI takes the advantage of the linear relationship between spherical harmonic bases and PCA bases. It extends the illumination estimation of QI from single point light source to any type of illumination conditions and is good for simulation of images under arbitrary illumination condition. Regarding LOG-DCT, it was developed based on the theory that illumination variation mainly lies in the



Figure 2: An example of face image decomposition using LTV

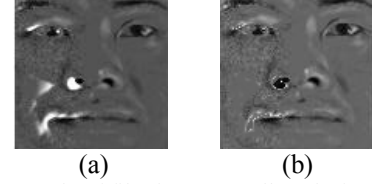


Figure 3: An example of filtering on small-scale feature image. (a): raw ρ ; (b): filtered ρ (i.e., ρ').

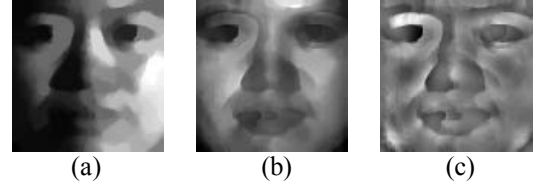


Figure 4: Examples of illumination normalization on S . (a): raw S ; (b): the normalized S using NPL-QI; (c): the normalized S using LOG-DCT.

low-frequency band. It is suggested that appropriate number of DCT coefficients in logarithm domain can be used to approximate the illumination variation, and these DCT coefficients are then truncated to reduce the effect of illumination.

2.4.1 Applying NPL-QI

In this section, non-point light quotient image (NPL-QI) [16] is employed to normalize the large-scale feature image S . Assume all face images have the same surface normal n . Utilizing principal components as the bases of illumination subspace, the NPL-QI of face y against face a is defined by

$$Q_y = \frac{r_y}{r_a} = \frac{I_y}{U \bullet l}, \quad (6)$$

where r_y and r_a are the albedo of face y and face a respectively, $U = [u_1, u_2, \dots, u_n]$ is the eigenvector matrix of training samples and $l = [l_1, l_2, \dots, l_n]^T$ is the estimated lighting that is the solution of the following equation:

$$f(l) = \min \|I_y - U \bullet l\| \quad (7)$$

The Q_y can be regarded as illumination invariant and used to synthesize the image under arbitrary illumination condition. Similarly, large-scale feature NPL-QI can be represented by

$$Q'_y = \frac{S_y}{U' \bullet I}. \quad (8)$$

Accordingly, in Eq.(8), U' is trained by large-scale feature images. Using large-scale feature NPL-QI, S_y can be transferred into the normal illumination condition by

$$S_{norm} = Q'_y \otimes U' \bullet I_{norm}, \quad (9)$$

where I_{norm} is the normal illumination trained by facial large-scale feature images under normal illumination condition. An example showing illumination normalization on S is illustrated in Fig. 4 (b).

2.4.2 Applying LOG-DCT

In this section, we demonstrate the use of LOG-DCT algorithm [13] for preprocessing on large-scale feature image. LOG-DCT is used for normalizing illumination by discarding low-frequency DCT coefficients in logarithm domain. For a face image, I and I' represent the face image under normal and varying illumination conditions respectively. Then S and S' are the corresponding large-scale feature images, i.e.,

$$\begin{aligned} I(x, y) &= \rho(x, y)S(x, y), \\ I'(x, y) &= \rho'(x, y)S'(x, y). \end{aligned} \quad (10)$$

According to Eq.(2), we have

$$\begin{aligned} S(x, y) &= R_i(x, y)L(x, y) \\ S'(x, y) &= R_i'(x, y)L'(x, y) \end{aligned} \quad (11)$$

Taking logarithm transform on Eq.(11) yields the following:

$$\begin{aligned} u'(x, y) &= \log S'(x, y) \\ &= \log R_i'(x, y) + \log L'(x, y) \\ &= \log R_i(x, y) + \log L(x, y) + \varepsilon(x, y) \\ &= \log S(x, y) + \varepsilon(x, y) \\ &= u(x, y) + \varepsilon(x, y) \end{aligned} \quad (12)$$

where $\varepsilon = \log L' - \log L$ is called the compensation term, the difference between the normal illumination and the estimated original illumination in the logarithm domain. From Eq.(12), it can be concluded that S can be obtained from S' by subtracting the compensation term ε in the logarithm domain.

Assume that the DCT coefficients of u' are $C(\alpha, \beta)$, $\alpha = 0, 1, \dots, M-1$, $\beta = 0, 1, \dots, N-1$. Then the inverse DCT is given by:

$$\begin{aligned} u'(x, y) &= \sum_{\alpha=0}^{M-1} \sum_{\beta=0}^{N-1} A(\alpha)A(\beta)C(\alpha, \beta) \\ &\quad \times \cos\left[\frac{\pi(2x+1)\alpha}{2M}\right] \cos\left[\frac{\pi(2y+1)\beta}{2N}\right] \\ &\stackrel{\Delta}{=} \sum_{\alpha=0}^{M-1} \sum_{\beta=0}^{N-1} E(\alpha, \beta) \end{aligned} \quad (13)$$

where A is the normalization coefficient function. In Eq.(13), setting n low-frequency DCT coefficients to be zero is equivalent to removing n low-frequency components, so we have

$$\begin{aligned} \hat{u}(x, y) &= \sum_{\alpha=0}^{M-1} \sum_{\beta=0}^{N-1} E(\alpha, \beta) - \sum_{\alpha=0}^{\sqrt{n}-1} \sum_{\beta=0}^{\sqrt{n}-1} E(\alpha, \beta) \\ &= u'(x, y) - \sum_{\alpha=0}^{\sqrt{n}-1} \sum_{\beta=0}^{\sqrt{n}-1} E(\alpha, \beta) \end{aligned} \quad (14)$$

In our experiment, 169 low-frequency DCT coefficients around the origin of coordinates in frequency domain are setting to be zero. Since it is assumed in LOG-DCT that illumination variations are mainly contained in the low-frequency components, the term $\sum_{\alpha=0}^{\sqrt{n}-1} \sum_{\beta=0}^{\sqrt{n}-1} E(\alpha, \beta)$ can be approximately regarded as the illumination compensation term ε , so \hat{u} is just the estimated normalized large-scale feature image in the logarithm domain. We therefore have

$$S_{norm}(x, y) = \exp \hat{u}(x, y). \quad (15)$$

The results of illumination normalization on S using this method are illustrated in Fig. 4 (c).

2.5. Reconstructing Normalized Image

Similar to Eq.(2), the normalized face image is finally reconstructed by combination of normalized large-scale feature image S_{norm} and smoothed small-scale feature image ρ' :

$$I_{norm}(x, y) = \rho'(x, y)S_{norm}(x, y). \quad (16)$$

Specifically, when using NPL-QI, according to Eq.(2) and (9), the reconstructed face image simulating normal illumination condition can be generated by

$$I_{norm} = \rho' \otimes (Q'_y \otimes U' \bullet I_{norm}). \quad (17)$$

When using LOG-DCT, the face image I_{norm} simulating normal illumination condition can be estimated by:

$$I_{norm}(x, y) = \rho'(x, y) \exp[\hat{u}(x, y)]. \quad (18)$$

3. Experimental results

In this section experiments are conducted to justify the following two points: (1) illumination normalization mainly performing on the large-scale feature image outperforms that on the whole image; (2) large-scale features are also useful for face recognition and should not be discarded. The performances of algorithms are evaluated in the aspects of face recognition and visual results of illuminated compensated images. For clear of presentation, we call the proposed framework as the reconstruction with normalized large- and small-scale feature images (RLS).

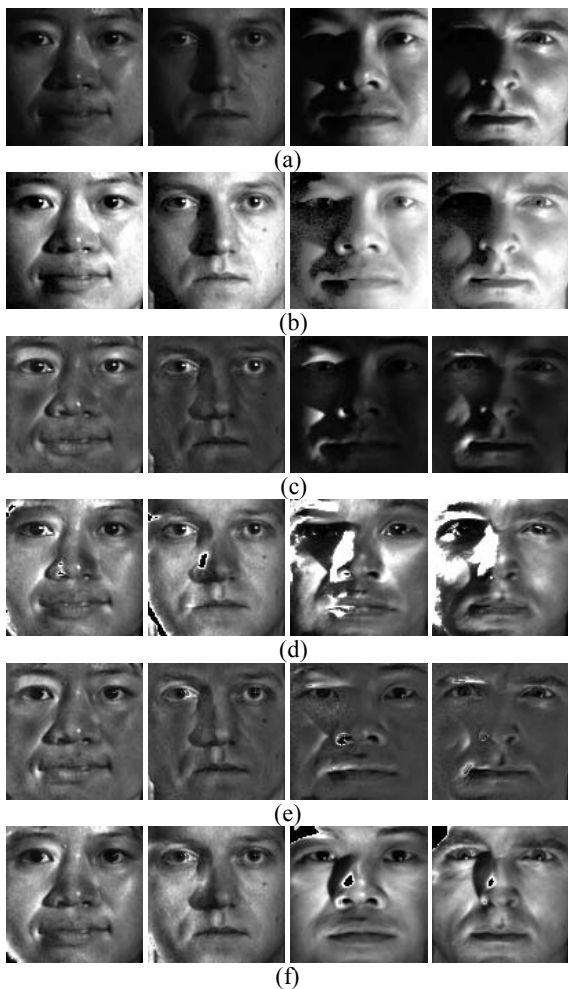


Figure 5: Illumination normalization using different techniques. (a): original images, (b): images normalized by HE, (c): images normalized by LOG-DCT, (d): images normalized by NPL-QI, (e): images normalized by RLS(LOG-DCT), (f): images normalized by RLS(NPL-QI).

Yale B [10], Extended Yale B and CMU PIE databases [18] are selected for evaluation. Images in Yale B are obtained from 10 individuals. Images are captured under 64 different lighting conditions from 9 pose views and are divided into 5 subsets (Set 1 to Set 5) according to the ranges of the illumination angles between the light source direction and the camera axis. In the Extended Yale B database, there are 16128 images of 28 human subjects captured under the same condition as Yale B. In the experiment, only frontal face images from these two databases are selected. The CMU PIE consists of 68 individuals. For testing, the frontal face images under 21 different illumination conditions with background lighting

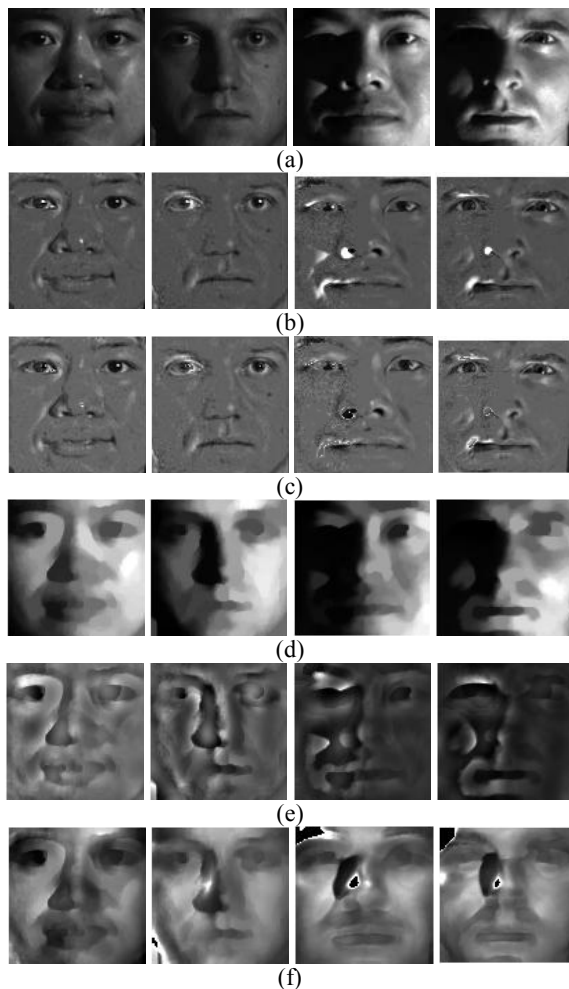


Figure 6: Illustration of the corresponding processing on large- and small-scale feature images of the images in Fig. 5 using the proposed framework. (a): original images, (b): small-scale feature image ρ , (c): filtered ρ (i.e., ρ'), (d): large-scale feature image S , (e): S normalized by LOG-DCT, (f): S normalized by NPL-QI.

off are selected. In our experiments, all images are simply aligned and each image is resized to 100×100 .

3.1. Illumination Normalization on Large-scale Feature Image vs. on Whole Image

In this experiment, we show that performing illumination normalization on large-scale image outperforms that on the whole image. In our framework, the threshold minimum filtering is performed on small-scale feature images, and the NPL-QI and LOG-DCT are respectively applied for illumination normalization on large-scale feature images. Accordingly, these two methods under our framework are respectively called RLS(NPL-QI)

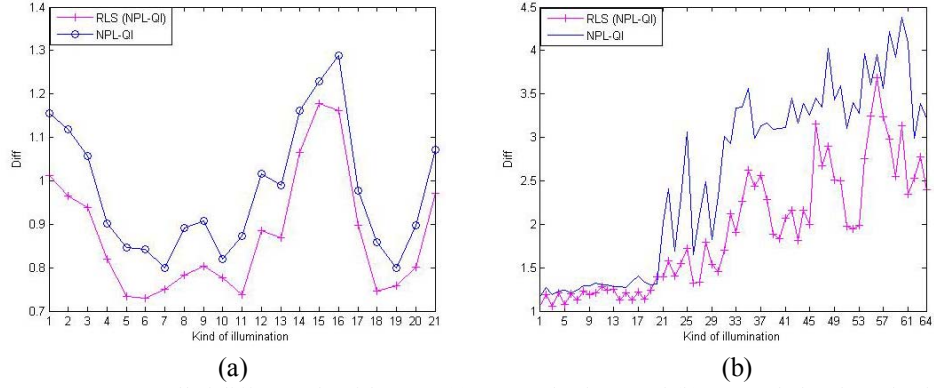


Figure 7: Average *Diff* of different algorithms on (a): CMU database and (b): Extended Yale B database.

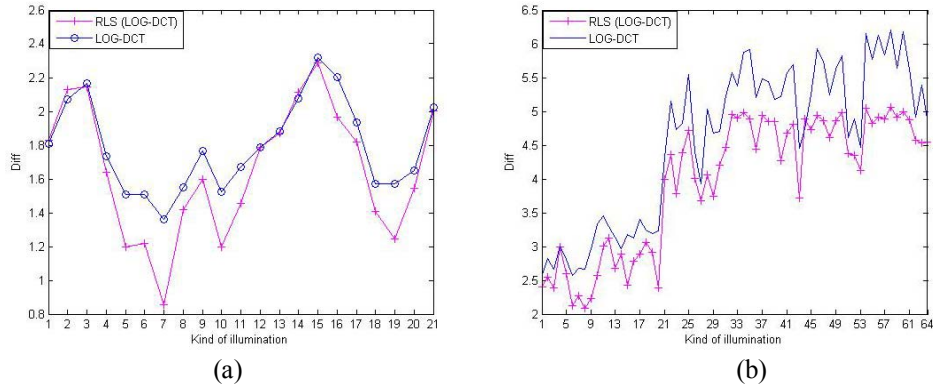


Figure 8: Average *Diff* of different algorithms on (a): CMU database and (b): Yale B + Extended Yale B database.

Method	Recognition Rate (%)			
	Set2	Set3	Set4	Set5
HE	93.5	39.9	22.9	10.5
NPL-QI	98.8	68.2	37.5	18.2
RLS (NPL-QI)	100	91.4	54.1	22.0

Table 1: Comparisons between different methods for illumination normalization on Extended Yale B.

Method	Recognition Rate (%)			
	Set2	Set3	Set4	Set5
HE	91.9	37.7	21.3	10.1
LOG-DCT	99.8	83.6	85.5	83.8
RLS (LOG-DCT)	100	87.1	87.6	84.8

Table 2: Comparisons between different methods for illumination normalization on "Yale B + Extended Yale B".

and RLS(LOG-DCT). We compare them with NPL-QI and LOG-DCT which are directly applied on whole face image. In addition, HE is also carried out as a baseline algorithm. For evaluation, we perform face recognition on normalized

Method	Recognition Rate (%)
HE	47.3
NPL-QI	88.4
RLS (NPL-QI)	95.3
LOG-DCT	99.8
RLS (LOG-DCT)	99.9

Table 3: Comparison between different methods for illumination normalization on CMU.

face images and also provide a measurement of the image quality.

We first compare the visual results of reconstructed images by different algorithms in Fig. 5. In addition, in Fig. 6, we show the image decomposition results, i.e., small-scale and large-scale feature images, and the illumination normalization results on them using our model. It is shown that our methods preserve the intrinsic facial structures well. As shown, when normalization is directly performed on the whole image, the normalized faces will lose more facial details, such as the edges and some textures with large illumination variation. Note that there are "local artifacts" in some normalized face images. These

local artifacts are caused by NPL-QI, as NPL-QI cannot perform well for shadows.

In addition, we propose an objective measurement for the visual quality of a normalized image as follows:

$$Diff = \frac{\|I_{standard} - I_{normalized}\|_2}{d}, \quad (19)$$

where $I_{normalized}$ and $I_{standard}$ denote the normalized image of a same subject and the corresponding image under normal illumination condition respectively, and d is the number of pixels in an image. For Yale B and Extended Yale B, the face image of any subject captured by the frontal camera is regarded as the normal one, i.e., $I_{standard}$ in Eq. (19). For CMU, the images captured by the 11th camera are the $I_{standard}$. The results are reported in Fig. 7 and 8, and the smaller the value $Diff$ is, the better the algorithm performs. As show, the proposed algorithms achieve lower $Diff$ values, and these also support the results shown in Fig. 5.

Finally, recognition results are reported for evaluation of the proposed framework. For each subject of the databases, only the image under normal illumination condition is registered as the reference image, and the rest images are treated as the query images. Nearest neighbor (NN) classifier is selected for classification, where normalized correlation is used as the similarity metric. The results are tabulated in tables 1, 2 and 3. The results show that the proposed scheme gets higher recognition rates. Note that when using NPL-QI in our experiments, all the 640 images from Yale B have to be used for training U and I_{norm} in Eq.(7)~(9), so the methods employed NPL-QL are only performed on Extended Yale B and CMU databases. Furthermore, according to [13], for the algorithms using LOG-DCT, logarithm images are directly used for recognition, i.e., the inverse logarithm transform step is skipped for face recognition. It can be seen that the algorithms under our framework gets higher recognition rates than the ones directly applying on the whole images.

The above experimental results indicate that when illumination normalization is mainly performed on large-scale feature image rather than the whole face image, higher recognition rates and better visual quality of reconstructed images are obtained.

3.2. Using vs. Discarding Large-scale features

Many methods only use the small-scale features for face recognition and discard the large-scale features. However, larger intrinsic facial structures which are also invariant to illumination may be contained in the large-scale features. In this experiment, we show large-scale features are useful for recognition and they should not be discarded. In the last section, LOG-DCT performs best in the aspect of recognition. So, to demonstrate the advantage of our framework, we select LOG-DCT to perform illumination

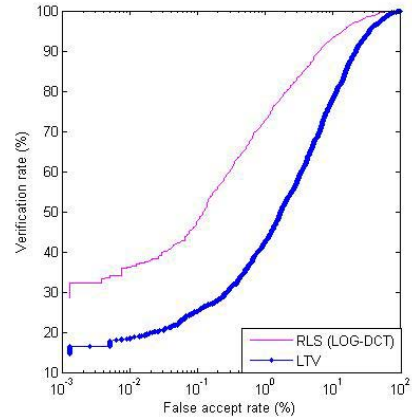


Figure 9: ROC curves of different methods on ‘‘Yale B + Extended Yale B’’ database.

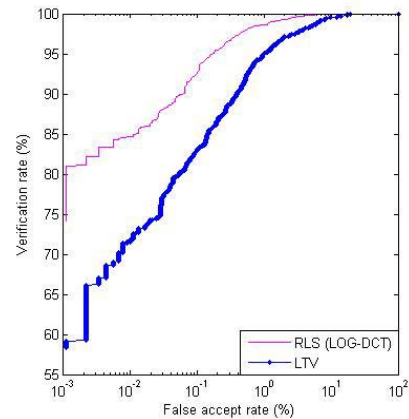


Figure 10: ROC curves of different methods on CMU database.

Method	Recognition Rate (%)				
	Yale B+Extended YaleB				CMU
	Set2	Set3	Set4	Set5	
LTV [5]	99.8	79.4	76.1	78.3	99.9
RLS(LOG-DCT)	100	87.1	87.6	84.8	99.9

Table 4: Comparison between different methods for illumination normalization.

normalization on the large-scale feature image and then use the reconstructed images for recognition. In this section, the performance of LTV model [5] is reported for comparison, and the results are tabulated in table 4. The setting of reference and query samples is the same as the last section. Chen et al. only use the small-scale feature images generated by LTV for recognition [5], while in our scheme, normalization is further performed on the large- and small-scale images and finally a reconstructed image is obtained. The results suggest that the proposed scheme gives higher

recognition rates on “Yale B+ Extended YaleB”. As LTV and RLS(LOG-DCT) get the same recognition rate on CMU, we further compare their ROC curves in Fig. 10. Also, the ROC curves on “YaleB+Extended YaleB” are given in Fig. 9, in which subset 2~5 are used as the testing data set. The figures show that significant improvements are obtained by RLS(LOG-DCT).

The above experimental results justify that only using small-scale features of face images for face recognition is not enough. Large-scale features are very important and should not be discarded.

4. Conclusions

A novel technique for face illumination normalization is developed in this paper. Rather than doing illumination normalization on the whole face image or discarding the large-scale features, the proposed framework performs illumination normalization on both large- and small-feature images independently. In particular, this paper demonstrates that large-scale features of face images are also important and useful for face recognition and obtaining good visual quality of normalized illuminated images. Moreover, we suggest performing illumination normalization mainly on the large-scale features rather than the whole face image meanwhile keeping the small intrinsic facial features which are invariant to illumination, as it would result in superior performance Utilizing the proposed framework, experimental results on CMU PIE and (Extended) YaleB databases are encouraging.

5. Acknowledgment

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