Normalization of Face Illumination Based on Large-and Small-Scale Features

Xiaohua Xie, Wei-Shi Zheng, *Member, IEEE*, Jianhuang Lai, Pong C. Yuen, *Senior Member, IEEE*, and Ching Y. Suen, *Life Fellow, IEEE*

***Abstract*—A face image can be represented by a combination of large-and small-scale features. It is well-known that the variations of illumination mainly affect the large-scale features (low-frequency components), and not so much the small-scale features. Therefore, in relevant existing methods only the small-scale features are extracted as illumination-invariant features for face recognition, while the large-scale intrinsic features are always ignored. In this paper, we argue that both large-and small-scale features of a face image are important for face restoration and recognition. Moreover, we suggest that illumination normalization should be performed mainly on the large-scale features of a face image rather than on the original face image. A novel method of normalizing both the Small-and Large-scale (S&L) features of a face image is proposed. In this method, a single face image is first decomposed into large-and small-scale features. After that, illumination normalization is mainly performed on the large-scale features, and only a minor correction is made on the small-scale features. Finally, a normalized face image is generated by combining the processed large-and small-scale features. In addition, an optional visual compensation step is suggested for improving the visual quality of the normalized image. Experiments on CMU-PIE, Extended Yale B, and FRGC 2.0 face databases show that by using the proposed method significantly better recognition performance and visual results can be obtained as compared to related state-of-the-art methods.**

***Index Terms*—Face recognition, illumination normalization, visual compensation.**

I. Introduction

It has been observed that illumination changes affect face image variations more significantly than face identity changes [1]. Both the face recognition vendor test (FRVT) 2002 [2] and FRVT 2006 [3] have revealed that large variations in illumination can seriously affect the performance of techniques for face recognition. Most existing methods for face recognition such as principal component analysis (PCA), independent component analysis (ICA), and linear discriminant analysis (LDA) are sensitive to illumination variations [9]. Hence face illumination normalization is a central problem in face recognition and face image processing as well, and many well-known algorithms have been developed to tackle this problem. These algorithms will be discussed, followed by our proposed method.

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X. Xie is with the School of Mathematics and Computational Science, Sun Yat-Sen University, Guangzhou 510275, China (e-mail: sysuxiexh@gmail.com).

W.-S. Zheng is with the School of Information Science and Technology, Sun Yat-sen University, Guangzhou, 510006, China. He is also with the Department of Computer Science, Queen Mary University of London, London E1 4NS, U.K. (e-mail: wszheng@ieee.org).

J. Lai is with the School of Information Science and Technology, Sun Yat-Sen University, Guangzhou 510006, China. He is also with the Guangdong Province Key Laboratory of Information Security, Guangzhou 510006, China (e-mail: stsljh@mail.sysu.edu.cn).

P. C. Yuen is with the Department of Computer Science, Hong Kong Baptist University, Hong Kong (e-mail: pcyuen@comp.hkbu.edu.hk).

C. Y. Suen is with the CENPARMI, Concordia University, Montreal, QC H3G 1M8, Canada (e-mail: suen@cenparmi.concordia.ca).

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A. Existing Algorithms and Analysis

Existing methods for illumination normalization can be divided into two categories: i) extracting illumination insensitive/invariant features, and ii) restoring frontal-illuminated face image. Accordingly, Fig. 1 shows the development of illumination normalization[1], and the two categories are described as follows.

1) Category I: Extracting Illumination Insensitive Features: In the earlier literature, researchers proposed to use simple descriptors such as logarithmic transformation, edge map, and image gradient for face recognition. These algorithms are easy to implement but the improvement in terms of the recognition rate is very limited. Recently, Zhang *et al.* developed a novel technique called Gradientfaces by extracting the illumination insensitive measure from the gradient domain [4]. In light of the development of time-frequency analysis, many researchers proposed to extract the illumination-insensitive features from the frequency domain. In most cases, the high-frequency subbands are used for recognition because they are insensitive to illumination variations. Representative works include using wavelet transform in Waveletface [40], extraction of Gabor feature [14], using discrete cosine transform (DCT) [41], using discrete Fourier transform (DFT) in the Spectroface [42], and the dual-tree complex wavelet transform (DT-CWT)-based method [5]. In the image space, the set of images under all possible lighting directions for an object with a fixed pose form a convex cone, which is called the illumination cone [23]. The illumination cone of a convex Lambertian object can be approximated by a low-dimension linear subspace. Therefore, many subspace-based methods have been proposed, such as quotient image (QI) [17] and Spherical Harmonic Presentation

[1]Due to the space limitation, only some foundational and representative works are listed in the figure. The given time in parentheses is mainly based on the publication time of the literature, and it may not be the exact time when the related work was proposed.

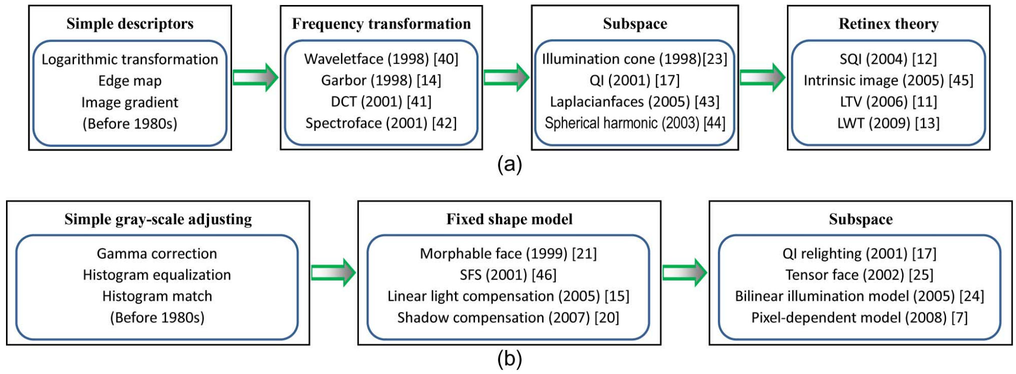

Fig. 1. Development of illumination normalization technologies on a face image: (a) Approaches for extracting the illumination-insensitive features. (b) Approaches for restoring the frontal-illuminated face image.

[44]. Based on the locality of preserving a projection, the proposed Laplacianfaces may also be used to reduce the effect of illumination [43]. The subspace-based methods can be effectively applied to tackle the illumination variation problem, but large numbers of training samples are always required in these methods.

The small-scale features of a face image are also considered to be invariant to illumination changes. For a face image, we call its small intrinsic structures as the small-scale features, (e.g., lines, edges and small-scale objects), and call its large intrinsic structures, illumination and shadows cast by big objects as the large-scale features. In many existing techniques, only the small-scale features are extracted for face recognition in order to avoid the illumination variation problem. Such methods mainly include Land's Retinex model [8] and its variants. Based on the Retinex theory, a face image is decomposed into its smoothed version and its illumination invariant features. To obtain such decomposition, the total variation model, Gauss filtering, weighted Gauss filtering, and wavelet transform are employed in logarithmic total variation (LTV) model [11], intrinsic image [45], self quotient image (SQI) [12], and logarithmic wavelet transform (LWT) [13], respectively. Among the methods of extracting the illumination insensitive/invariant features, the Retinex theory-based methods always perform better than the others. However, the large-scale features of a face image, which may also contain useful information for recognition, are always discarded in these methods. Furthermore, without the large-scale features, it is certainly hard to generate a frontal-illuminated image with a good visual quality.

2) Category II: Restoring Frontal-Illuminated Face Image: There are other methods that aim at restoring the face image with normal illumination, and these methods always perform illumination correction directly on the original face image. Early algorithms are used to make a simple gray-scale adjustment on the face image, e.g., Gamma correction, histogram equalization (HE), and histogram match (HM). The illumination conditions of the processed image have not been considered in these algorithms and it is difficult to attain satisfactory results with them. In contrast, the relationships between face images under different illumination conditions are investigated and these relationships are utilized to normalize the illumination in some advanced algorithms. Typical algorithms include morphing face [21], shape from shading (SFS) [46], linear lighting model-based illumination compensation [15], shadow compensation [20], and illumination compensation by truncating low frequency coefficients of DCT in the logarithm domain [16]. Rational results can be produced by using these algorithms, but a strict alignment upon a fixed shape model is always needed. However, strict alignment is also challenging under varying illuminations. Based on the illumination subspace theory, many relighting methods have been proposed, e.g., quotient image (QI) relighting method [17], spherical harmonic basis morphable model (SHBMM) [22], tensor face [25], bilinear illumination model [24], Harmonic relighting [49], and pixel-dependent relighting model [7]. By applying these relighting algorithms, an image by simulating arbitrary illumination conditions can be generated. In particular, the QI relighting method [17] and the nonpoint light quotient image relighting method (NPL-QI) [18], [33] rely on the assumption that the quotient image, which is the ratio of albedo between a test face and a given face, is invariant to illumination. In summary, methods of restoring a frontal-illuminated face image always process illumination normalization directly on the original face image. However, this operation results in distortion to the illumination-invariant features.

Besides the above two typical approaches, some other researchers proposed to fuse the local and holistic features for face recognition [26]–[29] against illumination variations. They primarily focus on extracting and fusing multiple illumination-insensitive features but still do not consider using large-scale features for the normalization problem. Du *et al.* proposed wavelet-based illumination normalization [30]. They applied HE on the low frequency coefficients and enlarged the high frequency coefficient in a wavelet domain, and then obtained the normalized face image by using the inverse wavelet transform. This method, however, is not good for visual recovery because enlarging the high frequency coefficients will distort the facial structure. Due to the poor performance of HE for illumination normalization, the overall performance of their method is unsatisfactory.

B. Novelty of the Proposed Method

It is known that the small-scale features are illumination-invariant facial features, thus they should be kept during the illumination normalization process. As we will demonstrate later, the large-scale features contain useful information not only for synthesizing a normalized face image with a resulting good visual quality but also for obtaining a better recognition performance. Therefore, for illumination normalization, both large- and small-scale features should be used. However, how to incorporate both small- and large-scale features meanwhile keep or explore the intrinsic properties in both features is an issue that needs to be tackled. We propose a new method to solve the illumination problem in face restoration and recognition by using both large- and small-scale features of a face image. More specifically, we propose to normalize these features separately by first decomposing an input face image into the large- and small-scale features. Normalization is then performed mainly on the large-scale features, and only a smoothness operation is performed on the small-scale features. Finally, the processed large- and small-scale features are combined to generate a normalized face image. We show that two well-known techniques that include truncating DCT coefficients in the logarithmic domain (LOG-DCT) [16] and nonpoint light quotient image (NPL-QI) [33] can be significantly improved by incorporating the proposed method. Our preliminary work was first reported in [47].

In addition, due to the great challenge of illumination normalization in some tough situations, an optional but important step of using the $\mathrm{KPCA} + \mathrm{Pre\text{-}image}$ [19] based method for visual compensation is further suggested to enhance the visual quality of a normalized image.

The rest of this paper is organized as follows: In Section II, the novel illumination normalization method is presented. In Section III, experimental results are shown. Finally, the conclusion of this paper is given in Section IV.

II. Proposed Illumination Normalization Method

In many illumination normalization algorithms, the large-scale features are discarded or all kind of features are processed in a same way. In contrast, this paper focuses on developing a novel method to process the small-and large-scale features separately for face illumination normalization. The overview and each step of the proposed method are described in this section.

A. Motivation and Method Overview

Based on the Lambertian reflectance theory [39], the intension of a face image I can be described by

$$I(x,y) = R(x,y)L(x,y), \tag{1}$$

where R is the reflectance component (albedo) and L is the illumination effect. R depends only on the surface material of an object, so it is the intrinsic representation of a face image. Many existing methods attempt to extract the reflectance component for face recognition. Unfortunately, estimating R from I is an ill-posed problem [34]. To solve this problem, Chen *et al.* proposed a more practical model [11]. In this model, R_l is denoted as the albedo of large scale skin areas and background. Then, based on (1), the following decomposition is obtained:

$$\begin{aligned} I(x,y) &= R(x,y)L(x,y) \\ &= \left(\frac{R(x,y)}{R_l(x,y)}\right)(R_l(x,y)L(x,y)) \\ &= \rho(x,y)S(x,y). \end{aligned} \tag{2}$$

TABLE I
Face Recognition on Yale B Database, Using Only the Large-Scale Features

Recognition Rates (%)				
Set 1	Set 2	Set 3	Set 4	Set 5
96.67	85.83	50.00	29.29	23.16

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

Based on the Lamberitian reflectance theory, illumination variations mainly affect the low-frequency components of a face image [17]. Accordingly, illumination variations mainly affect the large-scale features of a face image and it is important to retain the invariant features such as the small-scale features in illumination normalization. Besides the extrinsic illumination and shadows cast by bigger objects, the larger intrinsic facial structures could also be present in the large-scale features. This implies that large-scale features of different subjects can be distinguished to a certain degree. To verify this point, we conducted an experiment of face recognition using only large-scale features as facial features. The frontal face images of 10 objects from the Yale B database [23] were used in the experiment.[2] Each image was decomposed into small-and large-scale features. Only the large-scale features were directly used as facial features for recognition. For each subject, only one frontal-illuminated image was registered as the reference image, and the remaining images were treated as the query images. The recognition results are shown in Table I. As shown, for the images with small variations in illumination, i.e., in Sets 1–2, quite high recognition rates of 96.67% and 85.83% were obtained, respectively. For the images with extreme illumination changes, i.e., on Sets 4–5, the recognition rates are still much higher than the average expectancy, i.e., 10%. The experimental results suggest that the large-scale features contain a lot of useful information for face recognition. This conclusion is also intuitively supported in Figs. 8 and 9 in Section III-A, which show that the large-scale features present the individual facial structures.

The above analysis suggests that both small-and large-scale features are useful for face recognition and synthesis. Therefore, finding a way of normalizing these features properly is very important. Based on the decomposition in (2), illumination normalization could be performed on S, while the small intrinsic facial features ρ could almost remain unchanged. Even some necessary processing is required on ρ, it is independent of that on S. To this end, we propose a new method for illumination normalization, which normalizes separately the large-and small-features, as follows:

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

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

[2]Yale B database contains the images of 10 objects from Extended Yale B database. More details will be introduced in Section III.

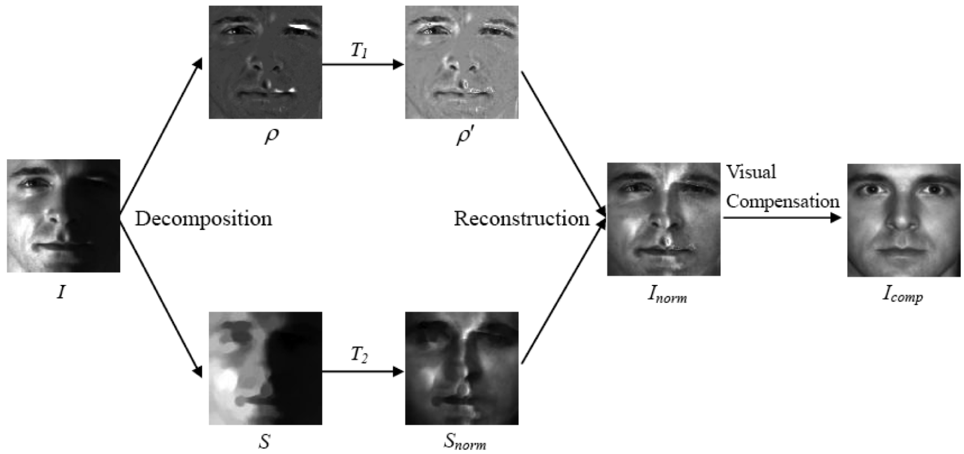

Fig. 2. Block diagram of the proposed method.

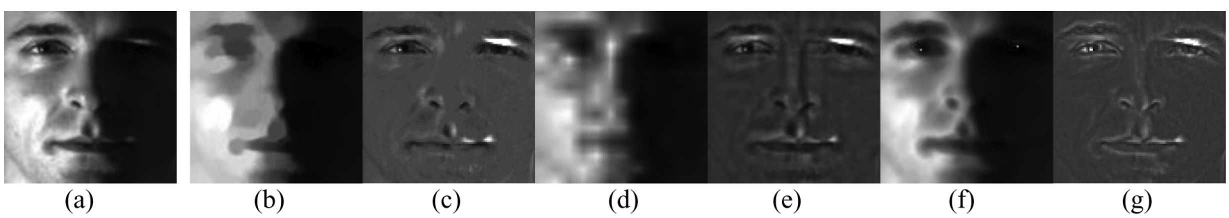

Fig. 3. Examples of face image decomposition, where (a) is the original face image; (b) and (c) are the results by using LTV; (d) and (e) are the results by using LWT; (f) and (g) are the results by using SQI. In these examples, (b), (d), and (f) are the large-scale features; (c), (e), and (g) are the small-scale features.

Fig. 2 shows a diagram of the proposed method. It consists of five steps: namely (a) face image decomposition, (b) smoothing on small-scale features (T_1), (c) illumination normalization on large-scale features (T_2), (d) reconstruction of normalized images, and (e) visual compensation. It should be pointed out that the step of visual compensation is not indispensable in some cases, e.g., face recognition. The details of each step are discussed in Sections II-B–II-F

B. Face Image Decomposition

In this subsection, we demonstrate how a face image can be decomposed into small-and large-scale features based on (2). First, by taking logarithm transform on both sides of (2), we have:

$$\begin{aligned} f &= \log I \\ &= \log \rho + \log S \\ &\triangleq v + u. \end{aligned} \tag{4}$$

The logarithm transform turns the multiplicative model into an additive one. Its advantages are two-fold: first, as an additive model, classical image estimation/decomposition techniques can be adopted; second, the logarithm of the luminance is a crude approximation to the perceived brightness and therefore the logarithm transform can partially reduce the effect of lighting. The logarithm preserves the structures, therefore v and u keep similar characters to ρ and S, respectively. To obtain the decomposition in (4), we utilize the LTV model. LTV has good capabilities of edge-preserving [11], so that it can extract illumination-invariant features better than many other existing methods. LTV estimates v and u as follows:

$$\begin{aligned} \hat{u} &= \arg\min_{u} \left\{ \int |\nabla u| + \lambda ||f-u||_{L^1} \right\} \\ \hat{v} &= f - \hat{u} \end{aligned} \tag{5}$$

where $\int |\nabla u|$ is the total variation of u, and λ is a scalar threshold. In our experiments, we set $\lambda = 0.4$ for the image of resolution size of 100×100. In (5), minimizing $\int |\nabla u|$ would enable the level sets of u to have simple boundaries, and minimizing $\|f-u\|_{L^1}$ would ensure the approximation of u to f. The interior-point second-order cone program (SOCP) algorithm was used to solve (5) in [11]. In this paper, we adopt the parametric maximum flow (PMF) algorithm [50] for the computation of the TV model. The PMF algorithm produces almost the same result as the SOCP algorithm, but its computation is much faster and is almost in real-time. After getting u and v, ρ and S can be estimated as follows:

$$S \approx \exp(\hat{u}), \quad \rho \approx \exp(\hat{v}). \tag{6}$$

There are also other feature-extraction methods for image decomposition, for example, the self quotient image (SQI) [12] and LWT [13]. The results of face image decomposition by different methods are illustrated in Fig. 3. It is worthy to note that, LWT may bring in blocking effects due to the isotropy of wavelet, and complex parameter selection is required for SQI. As shown in Fig. 3, the large-scale features do contain the identification information of the original face.

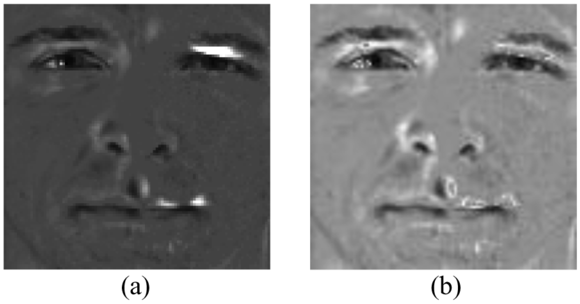

Fig. 4. Example of smoothing on small-scale features: (a) raw ρ; and (b) smoothed ρ (i.e., ρ').

C. Smoothing on Small-Scale Features

Since the estimation of reflectance is an ill-posed problem, the LTV decomposition may also bring in some undesirable results. As shown in Fig. 3, after face image decomposition, some light spots may appear in the estimated small-scale features ρ. Although the influence of these spots might be ignored for face recognition, it would have a negative effect on the visual quality of the reconstructed image. For this reason, we perform a threshold-average filtering on ρ to enhance the visual results.

The threshold-average filtering is defined as follows: suppose (x_0, y_0) is the center point of a convolution region. The average filter kernel will convolute only if $\rho(x_0, y_0) \geq \theta$, where θ is the threshold. In our experiment, a 10×10 mask is used and the θ is chosen individually for each ρ, such that the values of 99% of pixels are smaller than θ, and the values of the remaining 1% are larger than θ. In other words, this threshold-average filtering replaces the largest 1% values of ρ by the local average value. An example of the filtering result is illustrated in Fig. 4.

D. Illumination Normalization on Large-Scale Features

Recalling the discussion on (2), besides the extrinsic illumination and shadows cast by bigger objects, the larger intrinsic facial structures could also be present in the large-scale features. Therefore, the large-scale features S also contain the illumination invariant facial features, as supported by the demonstrated experiment in Section Section II. Furthermore, in order to produce the face image with a good visual quality, large-scale features have to be used. For these reasons, the large-scale features should be normalized, and the processing algorithm should be selected properly to meet the goal of illumination normalization, i.e., achieving good image quality or recognition performance. In this paper, two algorithms, namely NPL-QI [33] and truncating DCT coefficients in logarithm domain (LOG-DCT) [16] are adopted for demonstration purposes. We will show why and how these algorithms can be used to normalize the large-scale features. We also claim and give justification that performing illumination normalization by applying these algorithms mainly on large-scale features is more effective than on the original face image. The two mentioned algorithms are discussed below.

1) Applying NPL-QI: To restore a frontal-illuminated face image with a good visual quality, we adopted the NPL-QI to normalize the large-scale features S. NPL-QI takes advantage of the linear relationship between spherical harmonic bases and PCA bases. It extends the illumination estimation from a single point light source to any type of illumination condition and is good for simulating face images under arbitrary illuminating conditions.

The QI is defined as the ratio of albedo between a test face and a given face [17]. Assume that all faces have the same surface normal, and then the quotient image is equal to the image ratio between a test image and the image of the given face under the same lighting conditions. By modeling the illumination subspace using principal component analysis, the nonpoint light quotient image of face y is defined by:

$$Q_y = \frac{I_y}{U \bullet l} \tag{7}$$

where $U = [u_1, u_2, \ldots, u_n]$ is the eigenvector matrix of a given face under all lighting conditions, and $l = [l_1, l_2, \ldots, l_n]^T$ is the estimated lighting that is the solution of the following equation:

$$f(l) = \min \|I_y - U \bullet l\|. \tag{8}$$

Here, Q_y can be regarded as illumination invariant and can be used for face recognition.

When NLP-QI is performed on large-scale features, the large-scale-feature quotient image is represented by:

$$Q'_y = \frac{S_y}{U' \bullet l}. \tag{9}$$

Accordingly, in (9), U' is trained by using the large-scale features of a given face. In our experiments, all face images are only simply aligned. In order to obtain robust results, we suggest that the average version of several faces is used as the given face. By utilizing Q'_y, the large-scale features with an arbitrary illumination condition especially normal illumination condition can be generated by:

$$S_{norm} = Q'_y \otimes U' \bullet l_{norm} \tag{10}$$

where l_{norm} is the normal illumination trained by using the large-scale features under a normal illumination condition. An example of illumination normalization for S is illustrated in Fig. 5(b).

2) Applying LOG-DCT: LOG-DCT was developed based on the theory that illumination variations mainly lie in the low-frequency band. It has been suggested in [16] that the appropriate number of DCT coefficients in the logarithm domain can be used to approximate the illumination variations, and that these DCT coefficients can then be truncated to reduce the effect of illumination variation for face recognition. We demonstrate the usage of LOG-DCT algorithm for preprocessing the large-scale features.

For a face, I and I' are the images under normal and varying illumination conditions, respectively, and S_{norm} and S' are the corresponding large-scale features, accordingly:

$$\begin{aligned} I(x,y) &= \rho(x,y) S_{norm}(x,y) \\ I'(x,y) &= \rho(x,y) S'(x,y). \end{aligned} \tag{11}$$

According to (2), we have:

$$\begin{aligned} S_{norm}(x,y) &= R_l(x,y) L(x,y) \\ S'(x,y) &= R_l(x,y) L'(x,y) \end{aligned} \tag{12}$$

(a) (b) (c)

Fig. 5. Examples of illumination normalization on S: (a) raw S, (b) the S normalized by NPL-QI, and (c) the S normalized by LOG-DCT.

where L and L' are the uniform illumination and incident illumination, respectively. Performing the logarithm transform yields the following:

$$\begin{aligned}\log S'(x,y) &= \log R_l(x,y) + \log L'(x,y)\\ &= \log R_l(x,y) + \log L(x,y) + \varepsilon(x,y)\\ &= \log S_{norm}(x,y) + \varepsilon(x,y)\end{aligned} \tag{13}$$

where $\varepsilon = \log L' - \log L$ is called the error term, which describes the difference between the uniform illumination and the incident illumination in the logarithm domain. From (13), it can be concluded that S can be obtained from S' by subtracting the error term in the logarithm domain. Assume that the DCT coefficients of $\log S'$ are $C(\alpha,\beta)$, $\alpha = 0,1,\ldots,M-1$, $\beta = 0,1,\ldots,N-1$. Then, the inverse DCT is given by:

$$\begin{aligned}\log S'(x,y) &= \sum_{\alpha=0}^{M-1}\sum_{\beta=0}^{N-1} A(\alpha)A(\beta)C(\alpha,\beta)\cos\\ &\quad\times\left[\frac{\pi(2x+1)\alpha}{2M}\right]\cos\left[\frac{\pi(2y+1)\beta}{2N}\right]\\ &\triangleq \sum_{\alpha=0}^{M-1}\sum_{\beta=0}^{N-1} E(\alpha,\beta)\end{aligned} \tag{14}$$

where A is the normalization coefficient function. Since it is assumed that illumination variations are mainly contained in the low-frequency components, we can estimate the desired uniform large-scale features by removing some low-frequency components, and this is equivalent to setting n low-frequency DCT coefficients equal to zero:

$$\begin{aligned}\log S_{norm}(x,y) &= \log S'(x,y) - \varepsilon(x,y)\\ &\approx \sum_{\alpha=0}^{M-1}\sum_{\beta=0}^{N-1} E(\alpha,\beta)\\ &\quad - \sum_{\alpha=0}^{\sqrt{n}-1}\sum_{\beta=0}^{\sqrt{n}-1} E(\alpha,\beta).\end{aligned} \tag{15}$$

In our experiment, $169(= 13 \times 13)$ low-frequency DCT coefficients around the origin of coordinates in the frequency domain are set at zero. The results of illumination normalization on S by using this method are illustrated in Fig. 5(c). It should be pointed out that LOG-DCT is not favorable for image restoration due to the loss of some low-frequency information.

E. Reconstructing Normalized Image

According to (2), the normalized face image is finally reconstructed by combining the normalized large-scale features S_{norm} and the smoothed small-scale features ρ':

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

Specifically, for the NPL-QI based normalization, the final normalized image is obtained by:

$$I_{norm} = \rho' \otimes S_{norm} = \rho' \otimes Q'_y \otimes U' \bullet l_{norm}. \tag{17}$$

Since U and l_{norm} are not related to the individual identification, we can use only $\rho' \otimes Q'_y$ as facial features for face recognition.

F. Visual Compensation

After image decomposition, normalization of small-and large-scale features, and reconstruction, some visual flaws may appear in the normalized image. In order to further improve the visual quality of the processed image, a visual compensation operation should be considered.[3] In this paper, we selected the $\mathrm{KPCA} + \text{Pre-image}$ technology for visual compensation. The KPCA with preimage learning [19] is a well-known technique, which has been widely applied to face image analysis, such as image denoising [19], occlusion recovery and illumination normalization [31], [51]. Compared to linear PCA, the KPCA can process nonlinear structures and get better visual results. A detailed introduction to $\mathrm{KPCA} + \text{Pre-image}$ learning can be found in Appendix. The basic procedure of $\mathrm{KPCA}+\text{Pre-image}$ algorithm is illustrated in Fig. 6.[4] Particularly, we chose the regularized locality preserving learning (R-LPL) [32] for learning the preimage, since R-LPL requires no iteration and avoids numerical instability with unique solution.

In our experiments, we use the (nearly) frontal illuminated face images (five images per person as illustrated in Fig. 7) to train a kernel space and the KPCA subspace while maintaining 95% of the energy. Each testing image I_{norm} reconstructed by the previous four steps in our method is projected onto the KPCA subspace to eliminate the visual flaws, where

[3]For face recognition, this may not be necessary, and the visual compensation is only an optional processing.

[4]Since KPCA processes the data in the kernel feature space, a preimage learning algorithm is always needed to estimate the preimage of the processed data in the image space.

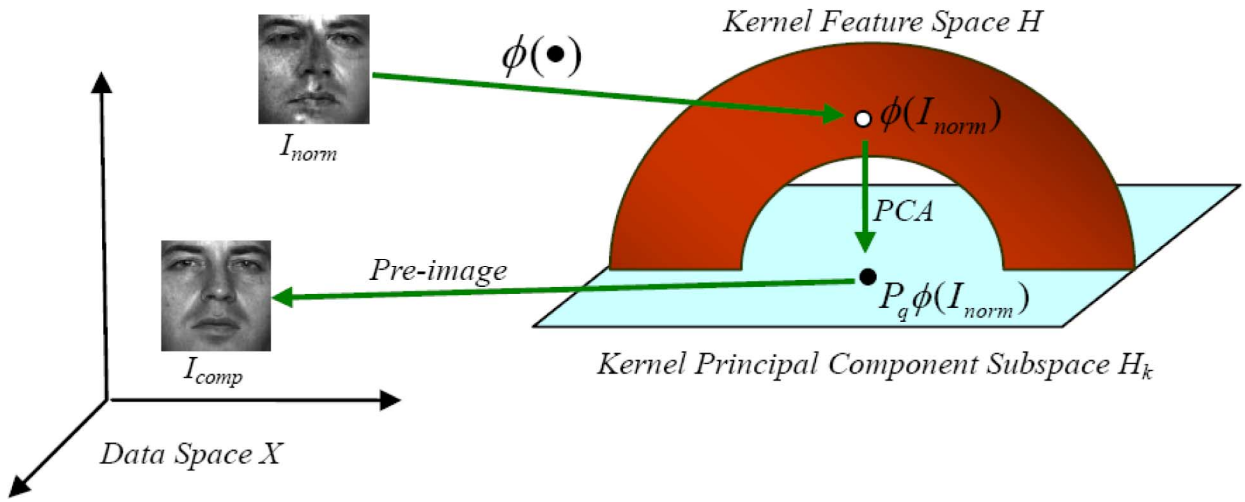

Fig. 6. Process of $\mathrm{KPCA} + \mathrm{Pre\text{-}image}$ method for visual compensation, where I_{norm} is the input image, $\phi(\bullet) : X \rightarrow H$ is the kernel mapping, $P_q\phi(I_{norm})$ is the projection of $\phi(I_{norm})$ onto the KPCA subspace, and I_{comp} is the learned preimage of $P_q\phi(I_{norm})$.

(a)

(b)

Fig. 7. Examples of training samples used for $\mathrm{KPCA} + \mathrm{Pre\text{-}image}$ algorithm, i.e., the (nearly) frontal illuminated face images. (a) Images from CMU-PIE database, (b) Images from Extended Yale B database.

TABLE II
SUBSETS OF EXTENDED YALE B [23]

Subsets	1	2	3	4	5
Lighting angle(°)	0~12	13~25	26~50	51~77	>77
Number of images	7×38=266	12×38=456	12×38=456	14×38=532	19×38=722

we denote such a projection as $P_q\phi(I_{norm})$. Then, the compensated image I_{comp} is obtained through learning the preimage of that projection.

III. Experimental Results

The presented experiment aims to validate the following two points: i) illumination normalization performed mainly on the large-scale features outperforms that on the original face image; and ii) large-scale features are useful for face image restoration as well as face recognition, and should not be discarded.

Extended Yale B [23], CMU-PIE [35], and FRGC 2.0 [48] face databases were selected for the evaluation. The images in Extended Yale B were obtained from 38 individuals and captured under 64 different lighting conditions from nine views. All face images were divided into five subsets according to the angle between the light source direction and the camera axis, as shown in Table II. In the experiment, we tested the algorithms on the frontal face images from Extended Yale B, in total $2432 (= 64 \times 38)$ images. The CMU-PIE database consists of 68 individuals. For testing, we selected the $1428 (= 21 \times 68)$ frontal face images under 21 different lighting conditions with background lighting off. The FRGC 2.0 database consists of 50,000 images captured from 625 subjects. The images were taken in different periods, under controlled and uncontrolled environments, with variations in illumination, expression, and ornaments (glasses). The controlled images were taken in a studio setting, under two lighting conditions and with two facial expressions. The uncontrolled images were taken in the varying illumination conditions, e.g., hallways, atriums, and outside. Only 275 subjects were selected in our experiment, each has five or more than

Fig. 8. Examples of illumination normalization for images from Extended Yale B and CMU-PIE databases: (a) original face images, (b) small-scale features, (c) large-scale features, (d) images normalized by NPL-QI, (e) images normalized by S&L (NPL-QI) without visual compensation, (f) images normalized by S&L (NPL-QI) with visual compensation using PCA, (g) images normalized by S&L (NPL-QI) with visual compensation using $\mathrm{KPCA} + \mathrm{Pre\text{-}image}$, and (h) original frontal-illuminated face images.

five controlled images and uncontrolled images with neutral expressions. Each selected image from the above-mentioned three databases was simply aligned and resized to 100×100.

We compared our method with LWT [13], LTV [11], the local binary patterns (LBP) [10], the direct LOG-DCT, and the direct NPL-QI algorithms. As notations, S&L(LOG-DCT) and S&L(NPL-QI) mean the specific algorithms by employing LOG-DCT and NPL-QI, respectively, to normalize the large-scale features in our method. The image quality assessment, face recognition, and in-depth investigation for visual compensation will be discussed, respectively, in Sections III-A–III-C.

A. *Quality Assessment of the Normalized Image*

In this experiment, we evaluate the related algorithms through the quality assessment of the normalized images. As previously discussed, the NPL-QI is favorable for face rendering and was considered in our experiments. For NPL-QI and S&L(NPL-QI), the average faces of 10 subjects from CMU-PIE were used to train the illumination subspace for the experiment on Extended Yale B; and the average faces of 10 subjects from Extended Yale B were used to train the illumination subspace for the experiment on CMU-PIE and FRGC 2.0. To evaluate the performance of visual compensation by using the $\mathrm{KPCA}+\mathrm{Pre\text{-}image}$ technique, we will show the results of S&L(NPL-QI) with and without visual compensation. For the $\mathrm{KPCA} + \mathrm{Pre\text{-}image}$ algorithm, the (nearly) frontal illumination images from different databases were used to train the kernel matrixes and subspaces, where for the Extended Yale B database, five images per subject from Set 1 with lighting angles of less than 12° were selected. For the CMU-PIE database, the images under the 8th, 9th, 11th, 12th, and 20th lighting conditions were selected (as shown in Fig. 7). Because FRGC 2.0 database does not specify

Fig. 9. Examples of illumination normalization for images from FRGC 2.0 database: (a) original face images, (b) small-scale features, (c) large-scale features, (d) images normalized by NPL-QI, and (e) images normalized by S&L (NPL-QI) without visual compensation. The left four columns are the controlled images, and the right four ones are the uncontrolled images.

the frontal-illuminated images, we did not perform the visual compensation on the images of this particular database.

We first compared the visual results of different methods. Figs. 8 and 9 illustrate the image decomposition results and the normalized results by applying different methods. As shown, by applying direct NPL-QI algorithm, the normalized faces lose some facial details, such as the edges and some textures. In contrast, our method removes the shadows and preserves much more intrinsic facial structures, no matter whether the illumination variations are large or not. Even though some visual flaws were observed, much better results were obtained for all test images by applying our method than the direct NPL-QI. Another interesting observation is that, for an input face image with closed eyes, the NPL-QI always outputs a normalized image with open eyes, while our method is able to maintain the original status of eyes (see the 1st, 4th, and 8th columns of Fig. 9).

The $\mathrm{KPCA}+\mathrm{Pre\text{-}image}$ based visual compensation helps remove some visual flaws such as light spots or corrupted blocks. In comparison, the results of PCA-based visual compensation are also shown in Fig. 8. By using PCA, the compensated results are fine in most cases; however, some faces are blurred or even distorted. This further strengthens the superiority of using the $\mathrm{KPCA} + \mathrm{Pre\text{-}image}$ method as visual compensation. In order to quantify the visual results, two kinds of typical image quality assessments, namely peak-signal-to-noise-ratio (PSNR) [6] and picture quality scale (PQS) [36] were used. PSNR is a kind of information-theoretic based assessment, and PQS is a kind of structure-based assessment. PQS is based on the perceptual properties of human vision and on extensive engineering experience with the observation of image disturbances due to image coding. It takes into account the properties of visual perception for both global features and localized disturbances. For each normalized image, we used the true frontal-illuminated image of the same individual as the reference image and computed the PSNR and PQS. A larger PSNR (PQS) value indicates a better visual quality of the normalized image. The average results from all test images from Extended Yale B and CMU-PIE databases with respect to different illumination conditions are reported in Figs. 10 and 11. As shown, the algorithms based on our method achieve higher PSNR and PQS values than the direct NPL-QI, regardless of visual compensation. Also, the visual compensation based on $\mathrm{KPCA} + \mathrm{Pre\text{-}image}$ gets better results than that based on PCA.

In summary, the above experimental results verify that when illumination normalization is mainly performed on the large-scale features rather than the original face image, a better visual quality of the reconstructed image can be obtained. The Section III-B will show that, along this approach, the recognition performance can also be improved.

B. Face Recognition Based on a Single Image

In this section, the face recognition results are reported. For each subject in the Extended Yale B and CMU-PIE databases, only a single image under the frontal-illuminated condition was registered as the reference (gallery) image, and the remaining images were treated as the query (probe) images. For the FRGC 2.0 database, the face recognition was performed in two subsets, i.e., controlled and uncontrolled subsets. For each subject, one controlled (uncontrolled) image was used as the reference image, and four controlled (uncontrolled) images were used as

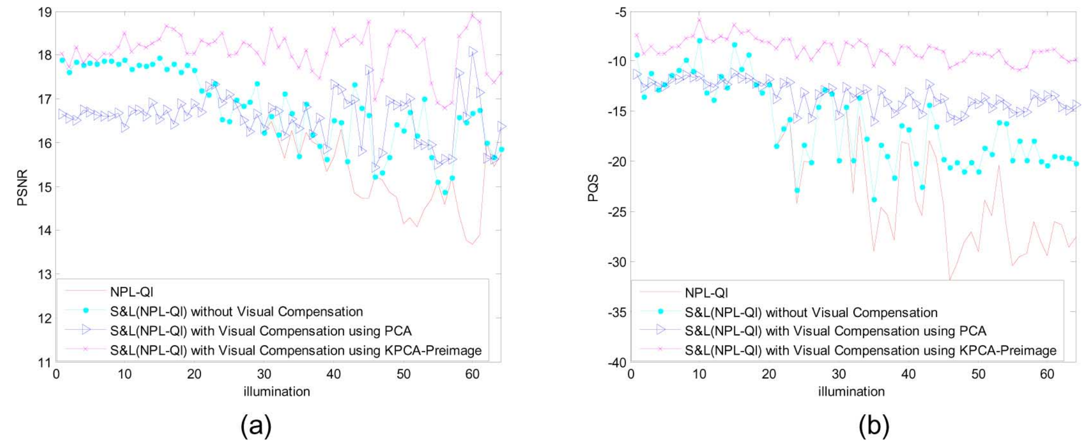

Fig. 10. Quality assessment of normalized images on Extended Yale B database: (a) the results evaluated by PSNR, and (b) the results evaluated by PQS.

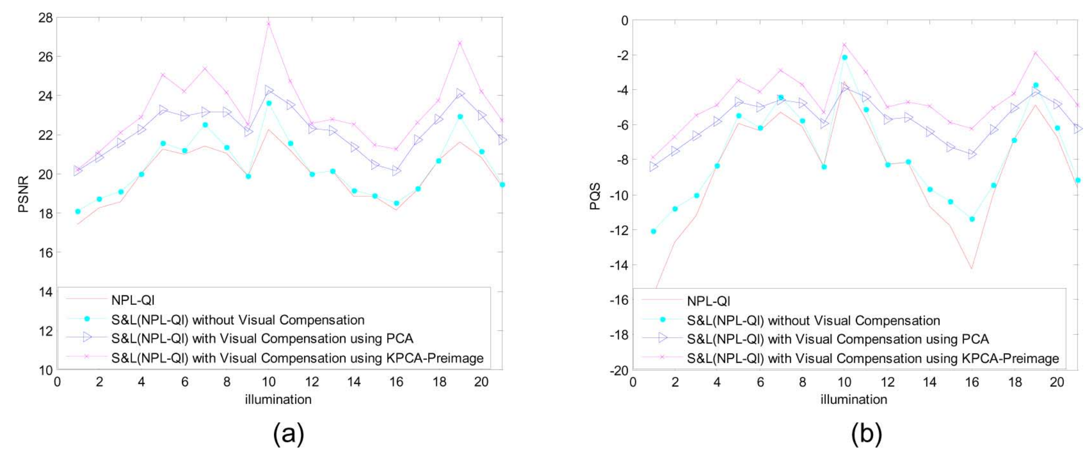

Fig. 11. Quality assessment of normalized images on CMU-PIE database: (a) the results evaluated by PSNR, and (b) the results evaluated by PQS.

TABLE III
COMPARISONS BETWEEN DIFFERENT METHODS FOR FACE RECOGNITION ON DIFFERENT DATABASES

Method	Recognition Rate (%)							
	CMU-PIE	FRGC 2.0 Controlled	FRGC 2.0 Uncontrolled	Extended Yale B				
				Set1	Set2	Set3	Set4	Set5
LBP	75.4	**88.9**	37.4	**100**	**100**	62.3	10.3	6.6
LWT	99.6	60.3	41.7	**100**	**100**	82.0	82.0	70.8
LTV	99.8	61.2	36.5	**100**	99.8	78.5	75.8	82.4
LOG-DCT	**99.9**	69.2	45.5	**100**	**100**	82.0	80.8	80.2
S&L(LOG-DCT)	**99.9**	76.1	52.3	**100**	**100**	86.0	85.3	**84.8**
NPL-QI	99.0	75.2	49.8	**100**	**100**	93.9	82.7	48.5
S&L(NPL-QI)	**99.9**	81.3	**57.5**	**100**	**100**	**96.7**	**87.0**	69.1

the query images. All reference and query images were processed by the same illumination-normalization algorithm and then used for recognition. Since our experiments focus on the effects of illumination normalization, the original pixel values of the normalized images were used as facial features for recognition, without further feature extraction or dimension reduction. For classification, the nearest neighbor (NN) classifier was selected, where the normalized correlation was used as the similarity metric.

We compared our two proposed algorithms, namely S&L(LOG-DCT) and S&L(NPL-QI), with direct LOG-DCT and NPL-QI. Also, as the state-of-the-art feature extraction algorithms, LWT, LTV, and LBP were included for comparative purposes. According to [16], for the algorithms using LOG-DCT, the logarithm images were directly used for recognition, i.e., the inverse logarithm transform step was skipped. For recognition, the optional visual compensation step was not used in our method and this will be discussed in Section III-C. Each method for face recognition was evaluated in the identification and verification modes.

The recognition rates of face identification by different methods are tabulated in Table III. As shown, the algorithms based on our method, S&L(LOG-DCT) and S&L(NPL-QI) (without visual compensation), respectively, produced higher

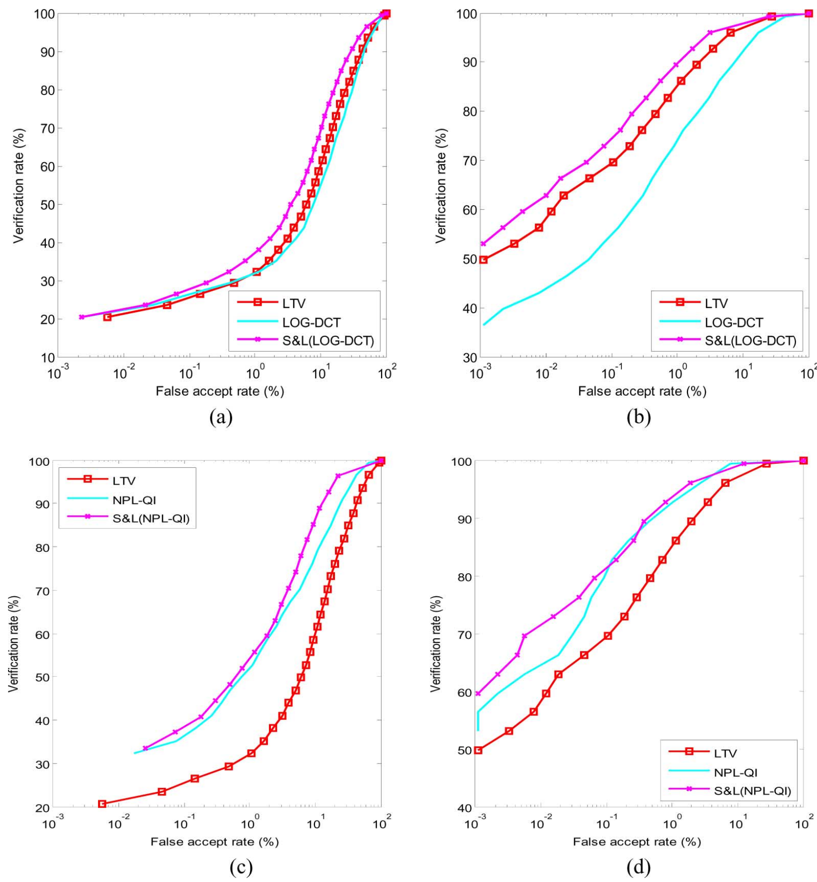

Fig. 12. ROC curves on (a) and (c): Extended Yale B database, and (b) and (d): CMU-PIE database.

recognition rates than direct LOG-DCT and NPL-DCT. Algorithms such as LWT and LTV only use the small-scale features for face recognition and they discard the large-scale features. It was experimentally verified in [11] that the LTV model outperformed several popular algorithms for face recognition, such as quotient illumination relighting (QIR) [37], QI [17], and SQI [12]. However, intrinsic facial structures in large-scale features which could also be invariant to illumination are omitted by LTV. Different from LTV and LWT, our method does preserve more invariant large-scale features. Table III shows that S&L(LOG-DCT) gets higher recognition rates compared to LTV and LWT on all databases. Except for the Set 5 of the Extended Yale B databse, the S&L(NPL-QI) also gets higher recognition rates than LTV and LWT. These results verify that small-scale features contain inadequate information for face recognition, while large-scale features are also useful for recognition and they should not be neglected. It is surprising that LBP gets the highest recognition rate for the controlled face images on the FRGC 2.0 database. This could be because other methods directly use the original pixel values as facial features, which inevitably reduces the recognition performance on a poorly aligned database such as FRGC 2.0. However, the recognition performance of LBP seriously drops on other subsets/databases with large lighting changes. This shows that LBP is sensitive to lighting changes.

Here, we also report the face recognition results in the verification mode. The ROC curves [38], which show the false accept rate (FAR) versus face verification rate (FVR), are illustrated in Figs. 12 and 13 for evaluating the face verification performances. The figures show that the algorithms based on our method obtain better verification performances than those directly applied on the original face images. Furthermore, significant improvements were obtained by S&L(LOG-DCT) or S&L(NPL-QI) against LTV.

C. Some In-Depth Discussions About Visual Compensation

In Section III-A, we have shown that visual compensation can improve the visual quality of the normalized images. In this section, we investigate the visual compensation step for face recognition. We suggest that the visual compensation step could be unnecessary for face recognition during the discussion in Section II-A. To verify this, we report the recognition results of S&L(NPL-QI) with visual compensation. Table IV shows the recognition rates and Fig. 14 displays the ROC curves.[5] All identification and verification results show that by adding visual compensation, the recognition performance is reduced rather than improved. One reason is that images of good visual quality could be locally smoother, so that the local discrepancy between face images of different objects becomes smaller. This indicates that a good visual quality may not lead to a good recognition

[5]The KPCA-$+\mathrm{Pre\text{-}image}$ technology needs several well-illuminated images per subject for training and we did not include these images in the testing sets for recognition. Other experimental settings were the same as those used in Section III-B.

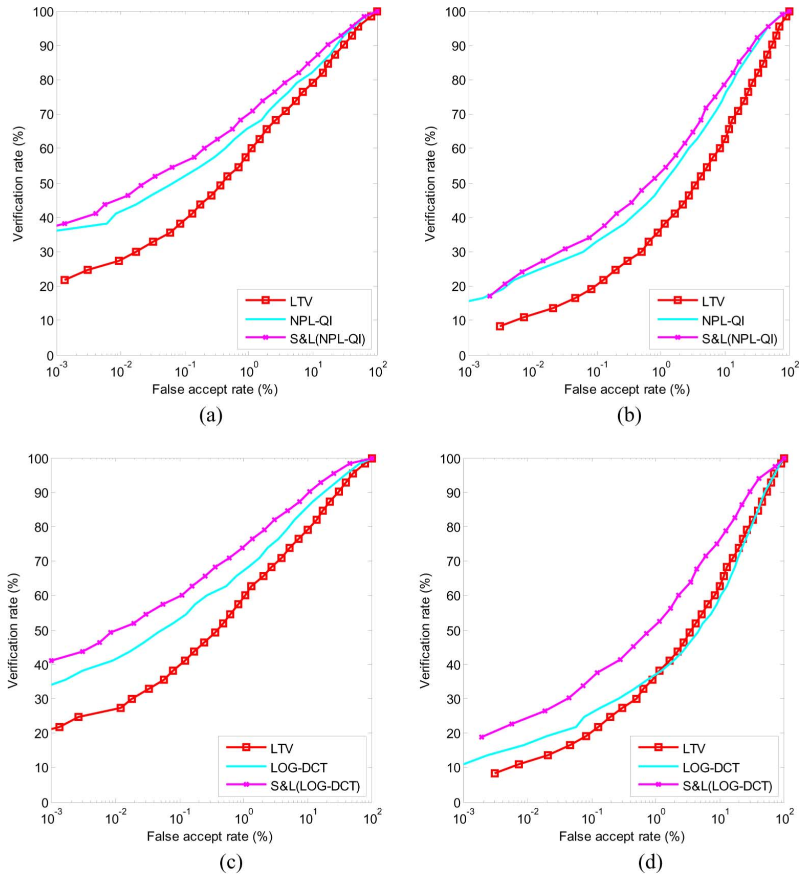

Fig. 13. ROC curves on (a) and (c): Controlled subset of FRGC 2.0 database, and (b) and (d): Uncontrolled subset of FRGC 2.0 database.

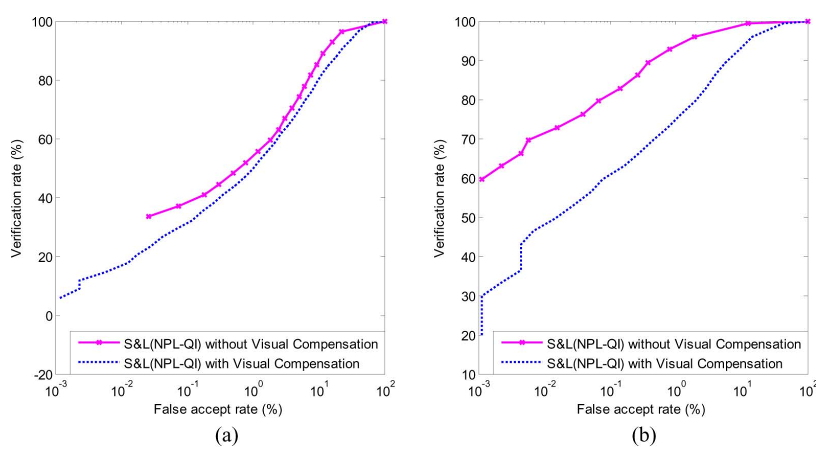

Fig. 14. ROC curves of using/not-using visual compensation on (a) Extended Yale B database, and (b) CMU-PIE database.

TABLE IV
COMPARISONS OF USING/NOT-USING VISUAL COMPENSATION FOR FACE RECOGNITION

Method	Recognition Rate (%)					
	CMU	Extended Yale B				
		Set1	Set2	Set3	Set4	Set5
S&L(NPL-QI) without Visual Compensation	**99.9**	**100**	**100**	**96.7**	**87.0**	**69.1**
S&L(NPL-QI) with Visual Compensation	73.8	*N/A*	92.3	78.9	51.7	32.8

performance. Hence, visual compensation is an optional step in our method.

IV. CONCLUSION

A novel technique for face illumination normalization has been developed in this paper. Rather than performing illumination normalization on the original face image or only using small-scale features while discarding the large-scale features, the proposed method performs illumination normalization separately on both large-and small-scale features of an image. In particular, we show that the large-scale features of face images are significantly important and useful for both face recognition and face restoration. Moreover, we demonstrate that illumination normalization should be mainly performed on the large-scale features rather than the original face image. By utilizing the proposed method, experimental results on Extended Yale B, CMU-PIE, and FRGC 2.0 databases are encouraging.

The proposed method includes five steps, namely image decomposition, correction of small-scale features, normalization of large-scale features, reconstruction, and visual compensation. These steps are all important and each of them could affect the subsequent ones. In the future, we will work on the improvement of operations for each step in our method, particularly for image decomposition and the normalization of large-scale features. Furthermore, the proposed method may be extended to face aging and expression issues, where the age-or expression-invariant facial features should be extracted and preserved.

APPENDIX

THE *R-LPL* BASED KPCA + Pre-image ALGORITHM*:* The preimage learning in kernel methods is a way to learn the preimage of a kernel feature point in the original input space, for example, the frontal-illuminated image space as in this paper. In the following paragraphs, we describe the procedure of preimage learning in KPCA, which can also be found in Fig. 6. A more detailed introduction can be found in [32].

Let X be the input image space and H be the Reproducing Kernel Hilbert Space associated with kernel $k(x,y)=\phi(x)^T\phi(y)$, where $x, y \in X$, and $\phi(\cdot)$ is an implicit mapping induced by kernel $k(\cdot,\cdot)$ such that $\phi(x): X \rightarrow H$. In this paper, the RBF kernel $k(x_i,x_j)=\exp\left(-\|x_i-x_j\|^2/c\right)$, $c = 10^4 \times 255^2$ was used. Let $P_q\phi(x)$ be the projection of $\phi(x)$ onto the subspace produced by a linear PCA. Suppose $x_1,\ldots,x_N \in X$ are N training samples and $\Phi = [\phi(x_1),\ldots,\phi(x_N)]$ is the data matrix and the mean value $u^\phi = (1/N)\Phi e$ in the kernel feature space, where $e=(1,\ldots,1)^T \in R^N$. We denote $U^{\phi^T} = \left(u_1^\phi,\ldots,u_q^\phi\right)^T$ as the transform of the principal component subspace. Then, for any $x \in X$, the projection of $\phi(x)$ onto the kernel PCA subspace $span\left\{u_1^\phi,\ldots,u_q^\phi\right\}$ is represented by:

$$\begin{aligned} P_q\phi(x) &= U^\phi U^{\phi^T}(\phi(x)-u^\Phi)+u^\Phi \\ &= \Phi P P^T \Phi^T\left(\phi(x)-\frac{1}{N}\Phi e\right)+\frac{1}{N}\Phi e \\ &= \Phi\gamma^x \end{aligned} \tag{18}$$

where $K=\Phi^T\Phi$ is the kernel matrix, P is the matrix such that $U^\phi = \Phi P$, $P \in R^{N\times q}$, and

$$\begin{aligned} \gamma^x &= (\gamma_1^x,\ldots,\gamma_N^x)^T \\ &= PP^T\Phi^T\phi(x)-\frac{1}{N}PP^TKe+\frac{1}{N}e \end{aligned} \tag{19}$$

After computing the projection $P_q\phi(x)$, i.e., the processed image feature in the high dimensional space, the task of preimage learning in kernel methods is to find its preimage $x_0 \in X$ such that $\phi(x_0)=P_q\phi(x)$.

Inspired by manifold learning, R-LPL treats H_k as a high dimensional space and X as its low dimensional space. The approximate preimage $\tilde{x}$ of $P_q\phi(x)$ can be treated as an embedding point of $P_q\phi(x)$ in X. Let $\phi(x_1),\ldots,\phi(x_s)$ be its s ($s=5$ in our experiments) distinct nearest neighbors from the training set in the kernel feature space. R-LPL first learns the local linear reconstruction weights $W_{\min}^x=(w_1^x,\ldots,w_s^x)^T$ as follows:

$$\begin{aligned} W_{\min}^x &= \arg\min_{W^x}\left\|\sum_{i=1}^s w_i^x\phi(\hat{x}_i)-p_q\phi(x)\right\|^2 \\ &\quad +\lambda\|W^x\|^2 \\ &= (\hat{\Phi}^T\hat{\Phi}+\lambda\times I)^{-1}\hat{\Phi}^TP_q\phi(x) \\ &= (\hat{\Phi}^T\hat{\Phi}+\lambda\times I)^{-1}\hat{\Phi}^T\Phi\gamma^x \end{aligned} \tag{20}$$

where λ ($\lambda = 0.0001$ in our experiments) is a regularized parameter and $\hat{\Phi} = (\phi(\hat{x}_1),\ldots,\phi(\hat{x}_s))$. Note that $\phi(x_1),\ldots,\phi(x_s)$ have their exact preimages $\hat{x}_1,\ldots,\hat{x}_s$ in the input image space X, respectively. By preserving the local linear reconstruction relationship, the preimage of $P_q\phi(x)$ is found by:

$$\tilde{x}=(\tilde{x}_1,\ldots,\tilde{x}_s)W_{\min}^x \tag{21}$$

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Xiaohua Xie was born in 1981. He received the M.S. degree in information and computing science and the Ph.D. degree in applied mathematics, both from Sun Yat-sen University, P.R. China.

He was a Visiting Student working with Prof. Ching Y. Suen at Concordia University, Montreal, QC, Canada. He has joined Shenzhen Institutes of Advanced Technology (SIAT), Chinese Academy of Science as an Assistant Professor in 2011. His current research interests include pattern recognition and computer vision, especially focusing on illumination normalization of image.

Wei-Shi Zheng (S'07–M'08) received the Ph.D. degree in applied mathematics at Sun Yat-Sen University, China, in 2008.

He has been a Postdoctoral Researcher on the European SAMURAI Research Project at the Department of Computer Science, Queen Mary University of London, UK. He has joined Sun Yat-sen University under the one-hundred-people program in 2011. His current research interests are in object association and categorization for visual surveillance. He is also interested in machine learning for discriminant/sparse feature extraction, kernel methods and transfer learning, and face image analysis.

Jianhuang Lai was born in 1964. He received the M.Sc. degree in applied mathematics in 1989 and the Ph.D. degree in mathematics in 1999 from Sun Yat-sen University, Guangzhou, China.

He joined Sun Yat-sen University in 1989, where currently he is a Professor with the Department of Automation, School of Information Science and Technology. He has published over 80 papers in the international journals, book chapters, and conferences. His current research interests are in the areas of digital image processing, pattern recognition, multimedia communication, wavelets and their applications. He has taken charge of more than five research projects, including NSF-Guangdong (U0835005), NSFC (number 60144001, 60 373 082, 60675016), the Key (Key grant) Project of Chinese Ministry of Education (number 105 134), and NSF of Guangdong, China (number 021 766, 06023194). He serves as a board member of the Image and Graphics Association of China and also serves as a board member and chairman of the Image and Graphics Association of Guangdong.

Pong C. Yuen (S'92–M'93–SM'11) received the B.Sc. degree in electronic engineering with first class honours in 1989 from City Polytechnic of Hong Kong, and his Ph.D. degree in Electrical and Electronic Engineering in 1993 from The University of Hong Kong.

He joined the Department of Computer Science, Hong Kong Baptist University in 1993 as an Assistant Professor and currently is a Professor. He was associated with the Laboratory of Imaging Science and Engineering, Department of Electrical Engineering. In 1998, He spent a six-month sabbatical leave in The University of Maryland Institute for Advanced Computer Studies (UMIACS), University of Maryland, College Park. He was associated with the Computer Vision Laboratory, CFAR. From June 2005 to January 2006, he was a Visiting Professor in the GRAVIR Laboratory (GRAphics, VIsion and Robotics), INRIA Rhone, Alpes, France. He was associated with PRIMA Group. He was the director of Croucher Advanced Study Institute (ASI) on biometric authentication in 2004 and the director of Croucher ASI on Biometric Security and Privacy in 2007. His current research interests include human face processing and recognition, biometric security and privacy, and human activity recognition.

Dr. Yuen was a recipient of the University Fellowship to visit The University of Sydney in 1996. Dr. Yuen has been actively involved in many international conferences as an organizing committee and/or technical program committee member. Recently, he was the track co-chair of International Conference on Pattern Recognition 2006. He is an editorial board member of *Pattern Recognition*.

Ching Y. Suen (M'66–SM'78–F'86–LF'08) received the M.Sc.(Eng.) degree from the University of Hong Kong and the Ph.D. degree from the University of British Columbia, Vancouver, BC, Canada.

He is the Director of CENPARMI, Concordia University, Montreal, QC, Canada, and the Concordia Chair on Artificial Intelligence and Pattern Recognition. He has guided/hosted 80 visiting scientists and professors, and has supervised 82 doctoral and master's graduates.

Dr. Suen is a Fellow of the IAPR, and the Academy of Sciences of the Royal Society of Canada. Currently, he is the Editor-in-Chief of the journal of *Pattern Recognition* and an Advisory or Associate Editor of four other journals. He has founded and organized numerous international conferences on pattern recognition, handwriting recognition, and document analysis. He has also founded the IAPR ICDAR Awards. He has served numerous professional societies as President, Vice-President, Governor, and Director. He has given 180 invited talks at various industries and academic institutions around the world, and has been the principal investigator or consultant of 30 industrial projects. His publications include four conference proceedings, 12 books and more than 480 papers of which many have been widely cited.