International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:5, No:5, 2011

Face Texture Reconstruction for Illumination Variant Face Recognition

Pengfei Xiong, Lei Huang, and Changping Liu

***Abstract*—**In illumination variant face recognition, existing methods extracting face albedo as light normalized image may lead to loss of extensive facial details, with light template discarded. To improve that, a novel approach for realistic facial texture reconstruction by combining original image and albedo image is proposed. First, light subspaces of different identities are established from the given reference face images; then by projecting the original and albedo image into each light subspace respectively, texture reference images with corresponding lighting are reconstructed and two texture subspaces are formed. According to the projections in texture subspaces, facial texture with normal light can be synthesized. Due to the combination of original image, facial details can be preserved with face albedo. In addition, image partition is applied to improve the synthesization performance. Experiments on Yale B and CMUPIE databases demonstrate that this algorithm outperforms the others both in image representation and in face recognition.

***Keywords*—**texture reconstruction, illumination, face recognition, subspaces

I. Introduction

Although face recognition technology being widely applied in practical systems, the effect of illumination variation is still one of the most limitations in the performance of recognition rate. It has been observed that the face appearance variation brought by illumination change is often larger than the face identity change does[1].

Generally, a face image appears as the combination of face albedo and light template[2]. While the face albedo is invariant to illumination change, many researchers tried to estimate face albedo for recognition. Methods, such as homomorphic filter[3], Discrete Cosine Transform(DCT)[4], regarded face albedo as high frequency component of the image, and eliminated the low frequency parts in frequency domain. Others, like Self Quotient Image(SQI)[5], Retinex[6], Logarithmic Total variation(LTV)[7], and Shadow Illuminator Process(SIP)[8], considered the face albedo as image noises, and subtracted light template from the whole image by image filtering and denoising. However, with the separation of light template, plenty of facial details are discarded together.

Xie[9] improved that by normalizing the illumination of these two parts respectively and combing them back, but the combination image easily appears as inhomogeneous holes or highlights while light template contains too little information to be rectified. Han[10] developed his algorithm with the same starting point. After face alignment, two images are transferred to each other's lighting by cross-combining their light templates and face albedos. His method depends on accurate locations of facial feature points, and is sensitive to face skin color.

Although performing well in the literature, these methods easily result in image distortions, due to the dependence of light template and face albedo. To overcome this shortcoming of image separation, a new algorithm that copes with the holistic image is proposed here instead. As is well known, any face image can be linearly represented in a subspace with its projection coefficients, which denotes the individual relationship between the image and subspace bases. If there exists another subspace including samples with the same person but normal lighting, facial texture image under normal illumination can be easily reconstructed by transferring the subspace bases. We establish these two subspaces based on the consistency of face albedo and original image. In particular, firstly light subspaces of different identities are formed from the given reference images and albedo image is extracted from the original image; then two group of texture reference images with the corresponding lighting of original and albedo images are reconstructed respectively by projecting them into each light subspace. While containing samples in correspondence with each other and under two valid light conditions, these texture reference images span two subspaces and face texture image can be synthesized. In addition, to deal with the face disalignment and improve the reconstruction performance, image blocking is applied.

Similar work have ever carried out by Lee[12] and Nishino[13], the former applying the projection coefficients in the lighting-selected texture subspaces for recognition, and the latter transferring the probe image into the illumination condition of gallery after estimating lighting from eyes reflection in the image. Comparing with them, firstly, detailed face texture image is recovered in our methods, which is more general for feature extraction, and is more applicable than projection coefficients recognition; then, our method doesn't depend on high resolution image for illumination estimation, and provides better performance on face recognition by lighting normalization than that in lighting transferring. Also, different from other outstanding methods, such as illumination cone[14], Spherical Harmonic Basis Morphable Models (SHBMM)[15], our method avoids the high computational complexity in 3D face shape recovery, and strengthens the applicability.

This paper is organized as follows: Section 2 analyzes the

Pengfei Xiong is with Graduate School and Insititute of Automation, Chinese Academy of Sciences, P.R.China, 100190, (phone: +86-010-62575198, e-mail: pengfei.xiong@ia.ac.cn)

Lei Huang, Changping Liu are with Insititute of Automation, Chinese Academy of Sciences, P.R.China, 100190, too.(e-mail: {lei.huang, changping.liu}@mails.ia.ac.cn).

related backgrounds and the principle of our algorithm. Section 3 presents each step in our algorithm in detail, and experiments and comparisons are carried out in Section 4. Finally, section 5 concludes this paper.

II. Algorithm Analysis

Based on the theory of Lambertian model, a valid face image can be described as the combination of face albedo, surface normal, and the illumination value. While in the image format, both the face albedo and surface normal are invariant to illumination variations, they can be combined as facial intrinsic features.

$$I_i = \rho_i \vec{n_i}^T \bullet \vec{l} = \vec{s_i}^T \bullet \vec{l} \tag{1}$$

Where I_i is the i_{th} pixel value of image I, ρ_i is its albedo, $\vec{n_i}$ and $\vec{s_i}$ are both 3*1 vectors for its surface normal and corresponding intrinsic characteristic respectively, and $\bullet$ is a dot product. $\vec{l}$ is also a 3*1 vector for the illumination value, which comprises from light intensity and light direction. The entire image has the same illumination.

In the same way, for a face image, its texture image is defined as the presentation of face under normalized light conditions. Here, $\overrightarrow{l_{norm}}$ denotes the normal illumination.

$$T_i = \rho_i \vec{n_i}^T \bullet \overrightarrow{l_{norm}} = \vec{s_i}^T \bullet \overrightarrow{l_{norm}} \tag{2}$$

With the unknown face features $\vec{s}$ and unknown light source $\vec{l}$, estimating face texture T from image I is an ill-posed question. The existing methods tried to simplify it. As light template is depicted as the projection of light source $\vec{l}$ along with the face surface normal $\vec{n}$, the original image can be described as the pointwise product of face albedo and light template based on (1). Then in log domain, the image can be easily divided and face albedo image is recovered by subtracting light template from the whole image.

$$L_i = \vec{n_i}^T \bullet \vec{l} \Rightarrow \log(L_i) = \log(\rho_i) + \log(L_i) \tag{3}$$

In this formula, L_i denotes the light template of i_{th} pixel. For ρ is insensitive to illumination change, these methods based on image separation perform well in the illumination invariant face recognition. However, while light template L depends on the face normal $\vec{n}$, plentiful facial details are lost accompany with the light template substraction. Face albedo image ρ being kept can't describe the integrate image features, and may impair face recognition performance to some extent.

To figure out this problem, the recovery of facial texture is required, which contains all the facial intrinsic features, and depicts the image under normal lighting. The algorithm of subspace is adopted. While images can be linearly represented in a low dimension subspace, linear equations below are established by projecting the original and face albedo image into the corresponding subspaces.

$$\begin{aligned} I_i &= \sum_j \alpha_j^I B_{i,j}^I = \sum_j \alpha_j^I (\overrightarrow{s_{i,j}^I}^T \bullet \vec{l}) \\ \rho_i &= \sum_j \alpha_j^\rho B_{i,j}^\rho = \sum_j \alpha_j^\rho (\overrightarrow{s_{i,j}^\rho}^T \bullet \overrightarrow{l_{norm}}) \end{aligned} \tag{4}$$

Where $\mathbf{B}^I = \{B_j^I\}$ and $\alpha^I = \{\alpha_j^I\}$ are the bases and coefficients of the original subspace, and $\mathbf{B}^\rho = \{B_j^\rho\}$ and $\alpha^\rho = \{\alpha_j^\rho\}$ are that of albedo subspace. In these two subspaces, samples are under the same lighting with the corresponding input image, and the numbers of bases are set to equal.

As the only difference between original face and texture image is the illumination variations, the facial texture can be synthesized based on the lighting transferred subspace $\mathbf{B}^{I'}$. $\mathbf{B}^\rho$ is applied here, while it provides a subspace with normal light. If $\mathbf{B}^\rho$ has the same identities with $\mathbf{B}^I$, which lead to the same intrinsic features $\mathbf{s}$, we can get $\mathbf{s}^I = \mathbf{s}^\rho$, and

$$\begin{aligned} T_i &= \rho_i \vec{n_i}^T \bullet \overrightarrow{l_{norm}} \\ &= \sum_j \alpha_j^I \overrightarrow{s_{i,j}^I}^T \bullet \overrightarrow{l_{norm}} \\ &= \sum_j \alpha_j^I \overrightarrow{s_{i,j}^\rho}^T \bullet \overrightarrow{l_{norm}} \\ &= \sum_j \alpha_j^I B_{i,j}^\rho \end{aligned} \tag{5}$$

According to (5), the conclusion is drawn that face texture image can be reconstructed from the projection coefficients of the original image and base images of the albedo image. Then the basis for facial texture reconstruction is transformed into the formation of the two subspaces $\mathbf{B}^I$ and $\mathbf{B}^\rho$ including samples with one-to-one correspondence and under two given lighting conditions.

Comparing with the algorithm[9], which can be formulated as

$$T_i = \rho_i F(L_i) = \rho_i F(\vec{n_i}^T \bullet \vec{l}) \tag{6}$$

where $F(x)$ denotes the process of light normalization, our method takes both the face albedo ρ and light template L in consideration. While extracting the face albedo, the left light template contains little facial information except the gradation of illumination intensity, which is difficult to tackle with. However, with the support of texture subspaces, the holistic image in our algorithm can be authentically rectified.

III. Algorithm flow

As described above, the requirement of two subspaces is crucial, in which, samples are different representations of the same individuals under two light conditions. Bilinear model[11] is inspired here, which formulates an estimation both in lighting and identity. This method improves that, avoiding the complex calculations of singular value decomposition(SVD) and realizing the formation of subspaces applying a group of given reference images. Firstly, light subspaces of each individual are constructed from its appearances under various illumination conditions. Then, by projecting the original and albedo images

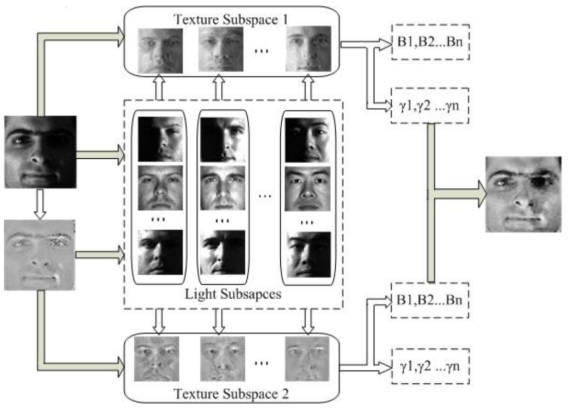


Fig. 1 The flow of face texture reconstruction

into each light subspace, two group of texture reference images with the original light and normal light are chosen. All these texture images with the same illumination span a texture subspace. While samples in these two texture subspace are one-to-one corresponding with each other, the realistic face texture can be reconstructed from them. In Fig.1, the flow of this algorithm is present.

A. Build light subspaces

Light subspaces are constituted with reference face images of the same identity under various light conditions. From these subspaces, reference texture images with lighting of the input image are reconstructed.

In each subspace, all samples belong to the same identity, and have the same intrinsic feature $\mathbf{s}$. Then based on

$$\mathbf{B}_l = [B_{l1}, B_{l2}, ..., B_{lM_l}] = \mathbf{s}^T \bullet [\vec{l_1}, \vec{l_2}, ..., \overrightarrow{l_{M_l}}] \tag{7}$$

In this formula, $\mathbf{s} = [\vec{s_1}, \vec{s_2}, ..., \vec{s_N}]$, and $\mathbf{B}_l$, a $N * M_l$ matrix, denotes the bases of light subspace. N is the number of image pixels, and M_l is the number of base images. Based on the Lambertian model, all anisotropic lights fit a subspace, and any light can be linearly represented by the light bases. Then with the projection coefficient $\overrightarrow{\beta_{cons}} = (\beta_1, \beta_1, ..., \beta_{M_l})^T$, the reference texture images can be reconstructed as

$$\overrightarrow{l_{cons}} = \sum_{i=1}^{M_l} \beta_i \bullet \vec{l_i}$$
$$I_{cons} = \mathbf{s}^T \bullet \overrightarrow{l_{cons}} = \mathbf{B}_l \bullet \overrightarrow{\beta_{cons}} \tag{8}$$

With the same intrinsic feature $\mathbf{s}$ in each subspace, the appearance difference between input image and subspace samples only depends on the illumination, then β_{cons} for the reconstructed image can be obtained by optimizing this difference,

$$\overrightarrow{\beta_{cons}} = \min\{\vec{\beta} \mid E = \| I_{in} - \mathbf{B}_l \bullet \vec{\beta} \|\} \tag{9}$$

The least square algorithm is applied for β_{cons} calculation.

$$\overrightarrow{\beta_{cons}} = (\mathbf{B}_l^T \bullet \mathbf{B}_l)^{-1} \bullet \mathbf{B}_l^T \bullet I_{in} \tag{10}$$

With this reconstruction coefficients, reference image with the same lighting of input image can be reconstructed from each light subspace. While the number of image pixels N fars outweigh the number of base images M_l, $\mathbf{B}_l$ is a column full rank matrix, and $\overrightarrow{\beta_{cons}}$ can achieve the optimal solution. The construction of light subspace depends on face images of the same person under varying lighting. While there is no limitation on the concrete light directions, reference images can be easily collected in practical application. In the formation of subspaces, several methods for bases have ever been carried out, such as Principal component analysis(PCA)[16], Sparse Representation[17]. In this paper, PCA is applied.

B. Build texture subspaces

Texture subspaces are built from face reference images of different identities under the same light conditions. For a valid image, its projection coefficients in the texture subspace are obtained to ensure that it can be accurately reconstruction from the subspace bases. Set the base images as $B_{t1}, B_{t2}, ..., B_{tM_t}$, which have the same illumination $\vec{l}$, then

$$\mathbf{B}_t = [B_{t1}, B_{t2}, ..., B_{tM_t}] = [s_1, s_2, ..., s_{M_t}]^T \bullet \vec{l} \tag{11}$$

With all images expended as $N * 1$ vectors, $\mathbf{B}_t$ is a $N * M_t$ matrix. N is also the number of image pixels, and M_t is the number of texture base images. In the corresponding texture subspace, the input image I_{in} has the same light l_{in} with the samples. After projecting, we can get the projection coefficients γ_{in} by optimizing the energy function.

$$\overrightarrow{\gamma_{in}} = \min\{\vec{\gamma} \mid E = \| I_{in} - \mathbf{B}_t \bullet \vec{\gamma} \|\} \tag{12}$$

The calculation of $\overrightarrow{\gamma_{in}}$ is similar to (10). With this projection coefficient, the input image can be reconstructed with the texture base images.

$$I_{in} \approx I_{cons} = \mathbf{B}_t \bullet \overrightarrow{\gamma_{in}} \tag{13}$$

As the number of base images M_t is much less than the number of image pixels N, the reconstructed image I_{cons} may lead to large differences from the original image I_{in}, so reducing the dimension of image pixels is necessary. Image blocking is an effective way. For each block of the image, the number of image pixels is deeply reduced, which ensures that the base image matrix $\mathbf{B}_t$ has full rank row, and decreases the reconstruction error. Image blocking has been used in [13][15] [18] and been proved as a meaningful way for image reconstruction.

To eliminate the boundaries between adjacent blocks, we apply the overlapped block in this paper. Set the image size as $H * W$, the block size as $H_s * W_s$, the overlap step as T_s, then image can be partitioned into $(\frac{(H - H_s)}{T_s} + 1) * (\frac{(W - W_s)}{T_s} + 1)$ blocks. As shown in Fig.2, red frames are labeled out as the borderlines of subimages, and the original image is divided into different regions. All images, including subspace samples and the input image, are decomposed in the same way, then each image block can be reconstructed with the same block of bases. Setting the p_{th} subimage as I_{in}^p, the projection coefficient $\overrightarrow{\gamma_{in}^p}$

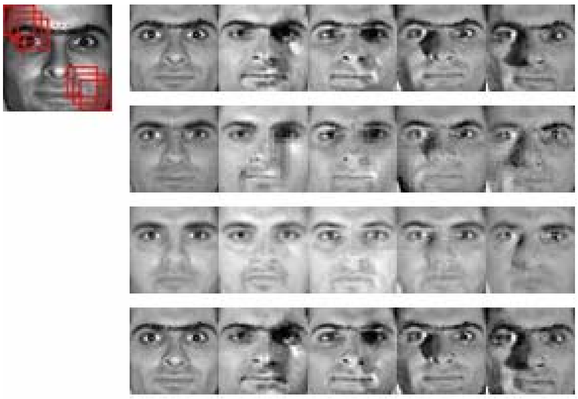


Fig. 2 face image segmentation. The red frames in the left face image are overlapped subimages. From top to bottom, the right four group images are image segmentations with block size 2*2, overlap step 1; block size 4*4, overlap step 2; block size 8*8, overlap step 4; and block size 2*2, overlap step 2

can be obtained from (13) with the corresponding p_{th} subimages of the bases.

With the projection coefficients, different regions of input image are reconstructed in turn. As these blocks are overlapped, pixel values in the reconstructed image are synthesized with weights.

$$v_{cons} = \sum_{i=1}^{t} \omega_i \bullet v_i \tag{14}$$

Where v_{cons} is one of the pixel value result in the reconstructed image, and v_i is the corresponding reconstruction value in the i_{th} block. t denotes the calculation times of this pixel in the process of image blocking. In each calculation, a weight ω is defined.

Different size of blocks result in different reconstruction results. The smaller blocks are, the less reconstruction error is generated. Reconstructed images with various blocks are depicted in Fig.2, which shows that with bigger blocks, images are more similar to average face of the subspace, and with smaller blocks, reconstructed images have more texture details. Also blocking results with and without overlapping is compared. From the first and the last row of Fig.2, it can be seen that segmenting with overlapped blocks provides smoother texture, and doesn't weaken the facial features.

C. Face texture reconstruction

Based on the formation of light subspaces and texture subspaces, face texture image can be cross-synthesised. Firstly, The face albedo image ρ_{in}, under the normal illumination conditions, is extracted from the original image I_{in}. LTV[7] is carried out for the extraction of face albedo. Although facial details are impaired in the albedo image, ρ_{in} eliminates the influence of light, and preserves the individual characteristics.

Then, two groups of texture reference images with the original lighting and normal light are chosen by projecting I_{in} and ρ_{in} into each light subspaces respectively. With these one-to-one image samples, original texture subspace and albedo texture subspace are formed. In the corresponding texture subspace, I_{in} and ρ_{in} are linearly represented as

$$\begin{aligned} I_{in} &= \sum_{i=1}^{t} \omega_i \bullet B_{ti}^{I} \bullet \overrightarrow{\gamma_i^{I}} \\ \rho_{in} &= \sum_{i=1}^{t} \omega_i \bullet B_{ti}^{\rho} \bullet \overrightarrow{\gamma_i^{\rho}} \end{aligned} \tag{15}$$

Where B_t^I and γ^I are bases and projection coefficients of the original texture subspace, B_t^ρ and γ^ρ are that of albedo texture subspace. t is the number of the block. With these parameters, face texture image can be reconstructed as

$$I_{norm} = \sum_{i=1}^{t} \omega_i \bullet B_{ti}^{\rho} \bullet \overrightarrow{\gamma_i^{I}} \tag{16}$$

Under the harsh lighting, regions of face images depicts black totally, which may result in the non-uniform bright or dark spots on the reconstructed texture image. In this paper, the luminance of the image is regulated to keep consistent before face texture reconstruction[19]. In face recognition application, this approach can be used as image preprocessing to rectify the light conditions of gallery and probe images, in order to construct a recognition environment with normal illumination.

IV. Experiments and Comparisons

To verify the validity of this method, we develop experiments on standard databases and compare it with other related algorithms. Extended Yale B database[14] and CMU PIE[20] database are selected as the test image databases, and Yale B[14] is set to the reference database. Images in Yale B and Extended Yale B are captured under 64 different lighting conditions from 9 pose views. To eliminate the influence of pose change, we only choose the frontal face images. There are 10 individuals in Yale B and 28 ones in Extended Yale B, then the reference database is constituted with 640 images, and 1792 faces is included in Extended Yale B test database. The CMU PIE consists of 68 human subjects. In testing, the frontal face images under 21 different illumination conditions with background lighting off are selected. After the location of the eyes, all images are aligned to the same mask and resized into 64*64 in our experiments. In Fig.3, some examples of Yale B and CMU PIE are given to describe the light variation of these images.

A. Presentation of reconstructed facial texture

In this experiment, we show that the visual results of our texture reconstruction method outperforms the other approachs based on image separation. To objectively evaluate the visual quality, a measurement for image difference between the ground truth and reconstruction image is defined as follows:

$$Diff = \frac{\sum_{i=1}^{N} (I_i^{cons} - I_i^{truth})^2}{N} \tag{17}$$

Where I^{truth} denotes the ground truth image with normal

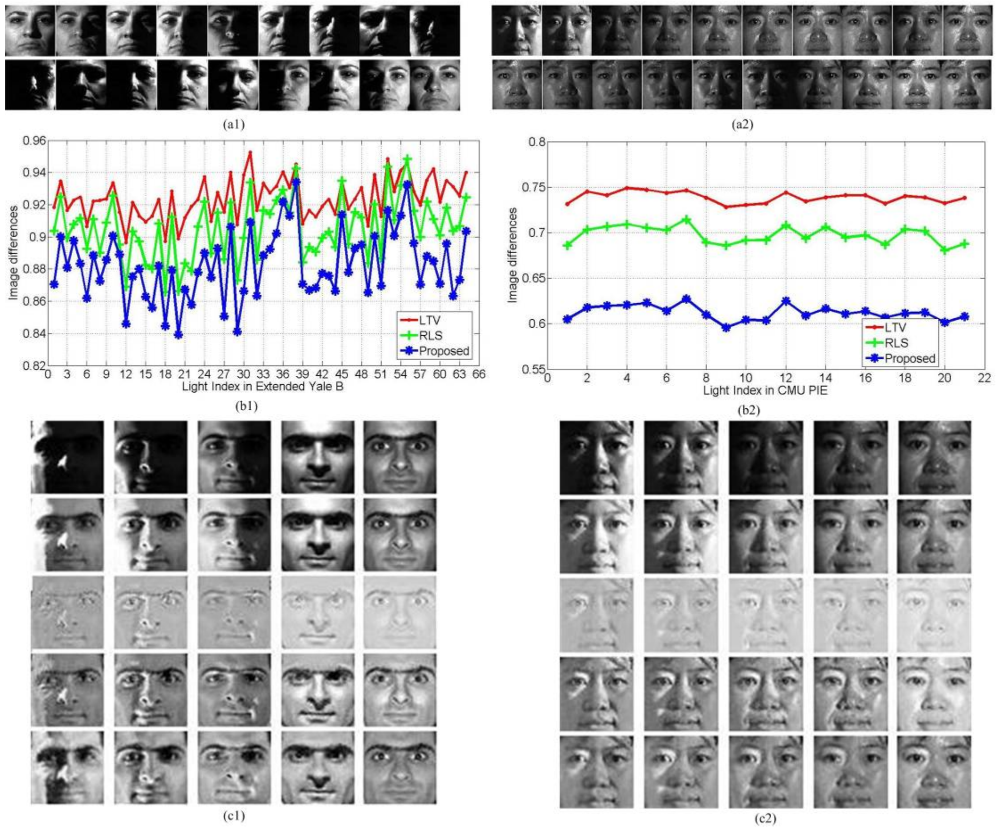


Fig. 3 comparisons of reconstruction texture representations. The left part is for Extended Yale B, and the right part is for CMU PIE. (a) depicts some examples in two databases; (b) describes the reconstruction errors by three different methods: LTV[7], RLS[9], and our proposed method; (c) presents different reconstruction images by five methods: original, GIA[19], LTV, RLS, and our proposed, from top to down

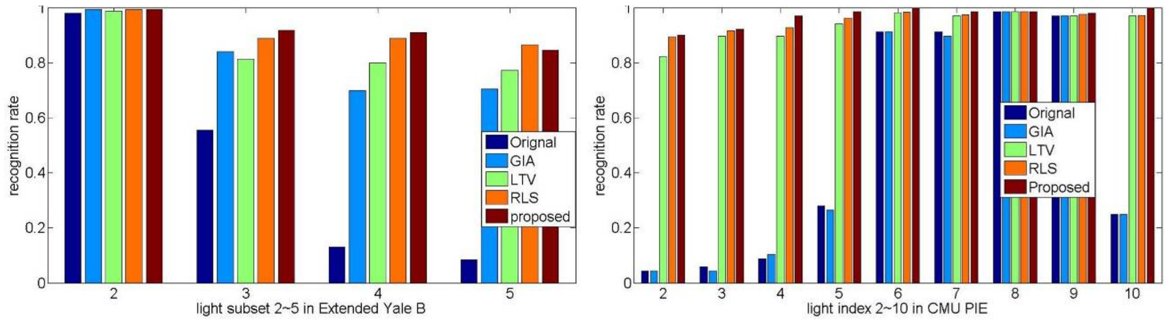
lighting, and I^{cons} is the illumination normalization image reconstructed from the same face under certain light. Both of the two images are normalized to eliminate the noise interference. For Extended Yale B, images with normal light I^{truth} are captured with all light directions 0; and for CMU PIE, ground truth images are captured by the 11th camera. In experiments, all images are divided into blocks with image size 2*2 and block step 1, and the reconstruction weight ω of each block is set to 1.

Face images under normal light conditions reconstructed from the other methods are selected as comparisons. To verify the reconstruction performance between our method and image separation, LTV[7] and Xie's[9] algorithm are carried out. While Xie provided two methods in his paper, the better one RLS(LOG-DCT) is chosen, which is named as RLS for short. The comparison results is present in Fig.3(b), in which, the left part shows the comparisons in Extended Yale B, and right part provides that for CMU PIE.

For the evaluation under different illumination conditions, all 64 light directions in Extended Yale B are sorted along with the light directions from 0 to 125. As shown, the reconstruction error of our proposed algorithm is the lowest among the three methods with any light condition. The result of LTV is highest, and RLS comes second, which support the results that methods of light template subtraction impair the texture of face image, and lead to more image distortions from the ground truth image. Also, in all of the 64 light conditions, reconstruction errors under harsh light is even less than that under slight light, as reported in Fig.3(b_1), lighting from 35 to 39 lead to bigger errors than the others while they are nearly normal light conditions. That is because of that images are smoother with the normal lighting, and the correlation between albedo image and light template are stronger, which result in worse performance of image separation. However, while smooth light brings little influence on the face recognition, the higher reconstruction errors won't weaken the recognition rate, which is also proved in the next section. Although presented as the similar distribution, the reconstruction errors in our method are all less than that of image separation, while the realistic face texture is reconstructed.

The same conclusion is drawn in CMU PIE, which showed in Fig.3(b_2). The light conditions are sorted in light index, and indexes 9-11 are the arbitrary lightings. While all original images in CMU PIE are smoother than ones in Extended Yale B, the total errors in former are less than that in the latter.

Also the visual results of reconstructed images by different methods are compared in Fig.3(c). For comparison, Global Illumination Adjustment(GIA)[19] used in our texture reconstruction is presented. As can be seen, plentiful facial



(1) (2)

Fig. 4 comparisons of illumination variant face recognition. The left part is for Extended Yale B, subset 2$\sim$5 are set as probe datasets; and the right part is for CMU PIE, light index 2$\sim$10 are tested. In each group of bar graphs, 5 algorithms are original, GIA[19], LTV[7], RLS[9], and our proposed method

details in images are lost in LTV. The combination of large- and small- feature images (RLS) improves on that, but leads to image noises. Also, the reconstruction images in RLS depicts different illumination intensities, while specular regions effect the image synthesized, as shown in the last two columns of Fig.3(c_1) and Fig.3(c_2), images are obviously brighter than others. Superior to them, our method provides detailed and smooth facial textures under various illuminations. However, the shadows under the hash lighting are still existing. While several image blocks are totally bright or dark with the hash light with image segmentation, it is inevitable to bring black patches on the reconstruction image, which needs extra processing to improve.

B. Recognition of reconstruction face texture

Besides the appearance presentation of reconstruction texture images, performance on face recognition is also evaluated. We also carry out several outstanding methods to compare with our algorithm. In the face recognition, all images are normalized and nearest neighbor classifier is selected as the classification. Normalized image distance is applied as the similarity metric, with I_g and I_p been set as gallery image and probe image,

$$corr = \sqrt{\sum_{i=1}^{N} (I_g(i) - I_p(i))^2} \tag{18}$$

In Extended Yale B database, all the 64 light conditions are divided into 5 subsets (subset1 to subset5). In this experiment, subset 1 is chosen as the gallery set, and the other subsets are set as the probe. Recognition results are reported in Fig.4(1). In each bar graph, five algorithms, original, GIA[19], LTV[7], RLS[9], and our proposed algorithm, are listed in turn. As shown, after our face texture reconstruction, the average recognition rate of all the four subsets increases from 0.437 to 0.917. In the first three subsets, our method performs better than all the other methods, especially LTV and RLS, which proves the validity of our method again. In subset 5, although the performance of our method is better than LTV, it slightly reduced comparing with RLS, from 0.864 to 0.845 with descend ratio 2%. That comes to the same defect in the last experiment. However, 2% is too small to affect the integral performance of face recognition, and the recognition rate of our algorithm with harsh light is still reliable enough.

The same experiment is carried out in CMU PIE, as shown in Fig.4(2). CMU PIE consists of images with 21 light conditions, and light 11 is the normal light. As the symmetry of the light directions, we choose images under light 2 to 10 conditions as the probe set, and ones with light 11 as the gallery. As depicted, the face recognition rate in CMU PIE reaches 0.975, after our method on face texture reconstruction. Under all of the 9 light conditions, our method performs better than all the others. As the light influence in CMU PIE is slighter then Extended Yale B, face texture reconstruction in CMU PIE doesn't repeat the invalidation in Extended Yale B. With any light, our method is superior to RLS.

In addition, to evaluate the performance between our algorithm with other methods applying subspaces, we carry out Nishio's[13] method as comparison. Following with his experiment, we select images with the same lighting as gallery and probe sets. The result is given in Fig.5, which showed that when lighting differences between gallery and probe images are remarkable, our algorithm has higher recognition rate obviously. The results support the idea that reconstruction errors of light normalization are smaller than that of illumination transferring. It is easy to be explained. Due to the dependence of light template and face albedo, illumination variations not only lead to different light templates, but also change the appearance of face albedo. Then light transferring on albedo images easily results in larger reconstruction errors. Better than his methods, our methods doesn't depend on high-resolution images for light direction estimation, and increases the average recognition rate from 0.941 to 0.959. With all the above experiments, the conclusion is justified that our algorithm not only reconstructs the realistic facial texture under various illuminations in appearance, but also provides more validity recognition rate in the illumination variant face recognition.

V. CONCLUSION

Face texture reconstruction to handle with illumination variant face recognition is developed in this paper. Based on the

	f8	f9	f11	f12	f13	f14	f15	f16	f17	avg
f8	1.000 / 1.000	1.000 / 0.985	1.000 / 0.985	0.969 / 1.000	0.938 / 0.941	0.938 / 0.938	0.846 / 0.911	0.677 / 0.735	0.547 / 0.677	0.879 / 0.908
f9	1.000 / 1.000	1.000 / 1.000	1.000 / 1.000	1.000 / 1.000	1.000 / 0.985	1.000 / 0.985	0.985 / 0.985	0.985 / 0.985	0.849 / 0.941	0.980 / 0.987
f11	1.000 / 1.000	1.000 / 1.000	1.000 / 1.000	1.000 / 0.985	0.985 / 0.985	1.000 / 0.985	0.955 / 0.955	0.726 / 0.926	0.722 / 0.867	0.938 / 0.967
f12	1.000 / 1.000	1.000 / 1.000	1.000 / 1.000	1.000 / 1.000	1.000 / 1.000	1.000 / 0.985	1.000 / 0.985	0.896 / 0.985	0.899 / 0.955	0.976 / 0.99
f13	0.892 / 0.941	1.000 / 1.000	0.910 / 0.955	1.000 / 0.985	1.000 / 1.000	1.000 / 0.985	0.985 / 1.000	0.896 / 0.955	0.833 / 0.911	0.946 / 0.970
f14	0.908 / 0.911	0.985 / 0.985	0.955 / 0.970	0.985 / 0.970	0.985 / 0.985	1.000 / 1.000	0.985 / 0.985	0.925 / 0.955	0.907 / 0.911	0.959 / 0.964
f15	0.723 / 0.867	0.924 / 0.911	0.821 / 0.897	1.000 / 0.985	1.000 / 0.985	1.000 / 1.000	1.000 / 0.970	0.985 / 0.985	0.963 / 0.955	0.935 / 0.951
f16	0.862 / 0.911	0.909 / 0.955	0.806 / 0.852	0.910 / 0.940	0.970 / 0.970	1.000 / 0.985	1.000 / 1.000	1.000 / 1.000	1.000 / 0.970	0.939 / 0.954
f17	0.736 / 0.806	0.887 / 0.897	0.852 / 0.911	0.926 / 0.955	0.926 / 0.926	0.963 / 0.985	1.000 / 1.000	1.000 / 1.000	1.000 / 1.000	0.921 / 0.942
avg	0.902 / 0.937	0.967 / 0.970	0.927 / 0.952	0.977 / 0.980	0.978 / 0.975	0.989 / 0.983	0.973 / 0.977	0.899 / 0.947	0.858 / 0.910	0.941 / 0.959

Fig. 5 comparisons of face recognition on CMU PIE between Nishio's[13] method and our proposed method. Rows denote the gallery set, and cols denote the probe set. In each table, the first result is Nishio's, and the second is ours

formation of subspaces, authentic texture images with normal light are obtained, which reduces the loss of facial details in the existing image separation approach. In particular, applying the consistency of original image and albedo image, groups of light and texture subspaces are successively established, and face textures are recovered from the linearly representation of the corresponding base images. Experiments on Extended Yale B and CMU PIE evaluate the validity of this approach, which provides the best performances not only on the image representation but also the face recognition, comparing with other outstanding algorithms. However, there still exists some shortcomings in the reconstruction under harsh light conditions. With the lack of image textures in some regions with harsh light, texture image represents invalidate reconstruction. How to improve this problem needs further study.

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