Illumination Transfer Using Homomorphic Wavelet Filtering and Its Application to Light-Insensitive Face Recognition

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Abstract

In this paper, we propose a novel homomorphic wavelet filtering based illumination transfer technique to change the dominant lighting of one face image (source face image) to another face image (reference face image). Specifically, in the proposed method, based on the "reflectance-illumination" imaging model, we first obtain an approximate estimate of the illumination component of the face image through a wavelet-based Multiresolution Analysis (MRA) in the logarithm domain of the input image. Then, a homomorphic filtering procedure is applied to improve the accuracy of the illumination component estimation. Finally, the source face image is re-lighted by substituting the estimated illumination component of the reference image for that of the source image. The proposed method is entirely an image processing based method without any 3D geometry modeling steps, so it is simple but effective. The method is also applied easily to illumination invariant face recognition by transferring a standard illumination to all the face images. Experimental results show that our method is quite effective for both illumination transfer and illumination-insensitive face recognition.

1. Introduction

Illumination transfer of face images based on image processing technique is drawing more and more attention in many application motivated academic researches [1], such as computer vision (CV), computer graphics (CG) and human-computer interaction (HCI). Recovering the lighting condition and 3-D geometry of a face from one single face image is an ill-posed problem, which determines that transferring the dominant illumination from a reference face image to a source face image is a rather challenging problem. However, in many cases, there is an urgent need for transferring the dominant illumination of an arbitrarily appointed reference image to a source image, such as virtual face image generation, human face analysis, face animation, illumination normalization or illumination generation of a person in virtual reality (VR).

Some approaches have been proposed to achieve illumination transfer or the similar goal, which can be roughly divided into two categories:

(1) 3D geometry model based methods [2-4]. Methods in this category usually first define a generic 3-D face model or geometric structure (landmarks or feature points), and then try to recover the parameters of the lighting condition and/or the 3D geometry model. Blanz and Vetter [3] matched a morphable 3D model (3DMM) to an image and got an estimate of the 3D geometry shape of the face and the lighting condition. Then, illumination transfer could be naturally achieved by changing the lighting parameters according to those of the reference face image. However, a time-consuming dense one-to-one correspondence map has to be calculated in 3DMM. Marschner and Greenberg [4] used an inverse lighting technique to get an estimate of the directional distribution of the incident light, and this information was used to achieve illumination transfer. But the assumption of distant light source needed by the inverse lighting is hardly satisfied in practice. Generally, these 3-D geometry model based methods can usually achieve higher accuracy and more photorealistic results; however, the model parameters of both the source image and the reference image have to be estimated, which is very hard and not accurate when given only one single face image.

(2) Image processing based methods [5-7]. In recent years, this category of method has attracted much attention. Shashua and Raviv [5] presented a class-based, image processing based method to implement relighting of general faces; however, their approach lacks general applicability since it is bound to one fixed pose of a given face. Stoschek [6] made an extension of Shashua and Raviv's work to arbitrary and continuous illumination directions, but requiring a set of training face images. Debevec et al. [7] calculated the reflection field of a face, which was then used to relight face images with arbitrary

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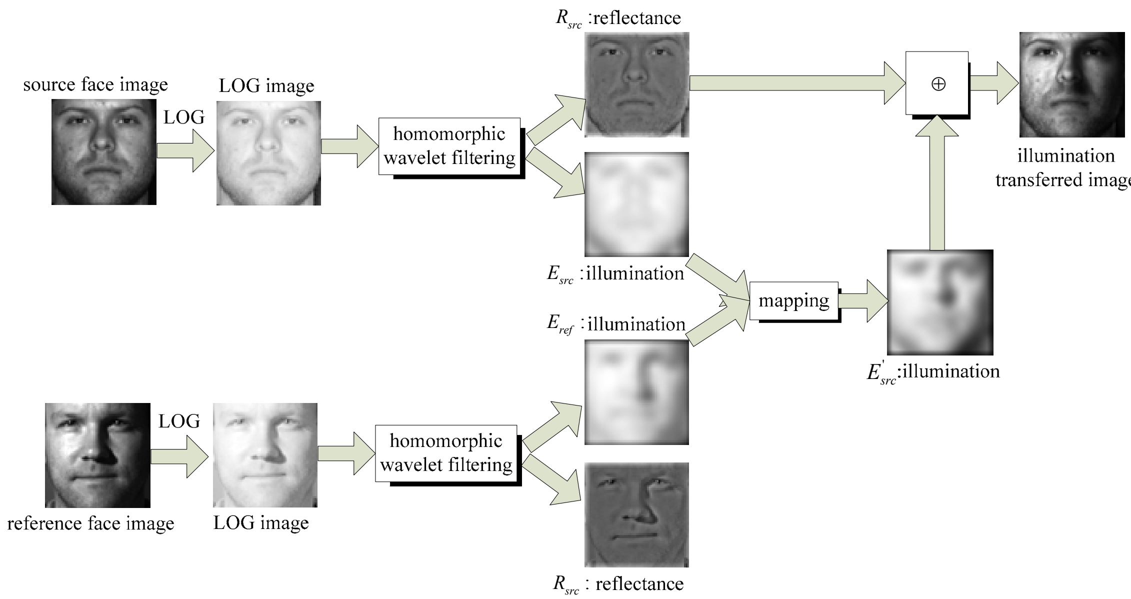

Figure 1: The flow chart of our proposed illumination transfer approach. First, we make a logarithm transform on both the source and reference face images. Next, a homomorphic wavelet filtering procedure is conducted on the LOG images to get the estimate of illumination component E and reflectance component R of source face image and reference face image. Then, the illumination component E of the source face is mapped to get target illumination E' according to that of the reference face. Last, inverse logarithm transform is performed on the LOG image, which combines target illumination component E' and reflectance component R of source face image together, to get the final illumination transferred face image.

reference lighting and viewpoint. However, this method relies on special equipment - light stage. Furthermore, when given only one single face image, the reflection field of either the source face image or the reference face image is not available.

By and large, although there are still a few inadequacies for image processing based methods, they tend to prove their robustness and effectiveness compared with 3D geometry model based methods. Especially they can deal with the typical illumination transfer problems where only one face image is available, and they do not need any prior information about the 3-D geometry and lighting conditions of the input face.

In this paper, we propose a simple but efficient image processing based illumination transfer technique for human face images without using any prior knowledge about lighting conditions or geometrical characteristic of source face image and reference face image. In this method, we describe human face images as a reflectance-illumination model [8] instead of a Lambertian model [9]. The overall flow chart of the proposed method is illustrated in Fig. 1. The core strategy is first performing multiresolution analysis (MRA) of wavelet on a LOG face image (source face image and reference face image) to get an approximate estimate for the illumination component E . Next, homomorphic filtering is performed on the detail coefficients of MRA to improve the estimate accuracy of illumination component E . Then, a mapping is employed to regularize the illumination component E of source face image according to that of the reference face image. Finally, inverse logarithm transform is performed to get the illumination transferred result.

The remaining parts of this paper are organized as follows: in Section 2, we describe the image processing based illumination transfer using homomorphic wavelet filtering in detail. Light insensitive face recognition based on our illumination transfer approach is presented in Section 3. And finally, we conclude this paper in Section 4.

2. Illumination transfer with homomorphic wavelet filtering

As shown in Fig. 1, the basic idea of the proposed method is separating the input face image into illumination component and reflectance component in the LOG domain by using homomorphic wavelet filtering, and then re-lighting the source image by adapting the source illumination component to the reference one. In this section, we sequentially describe the three main procedures of the proposed illumination transfer approach in three subsections respectively. Results of the illumination transfer are given in the last subsection.

2.1. Logarithm transform

As above mentioned, we adopt a

reflectance-illumination model instead of a Lambertian model:

$$i(x,y)=r(x,y)e(x,y) \quad (1)$$

where $i(x,y)$ is the face image, $r(x,y)$ is the reflectance component of the face surface which contains face texture and the component $e(x,y)$ contains information about illumination and the face shape.

Our goal is to separate and estimate the reflectance component r and the illumination/shape component e. To achieve this goal, a logarithm transform is first applied to the input image to convert the product of the two components into a sum:

$$\log i(x,y)=\log r(x,y)+\log e(x,y) \quad (2)$$

we rewrite it as follows:

$$I=R+E \quad (3)$$

where the symbols are defined as below:

$$\begin{aligned} I&=\log i(x,y)\\ R&=\log r(x,y)\\ E&=\log e(x,y) \end{aligned} \quad (4)$$

So for the source face image $i_{src}(x,y)$ and the reference image $i_{ref}(x,y)$, we have:

$$\begin{aligned} I_{src}&=R_{src}+E_{src}\\ I_{ref}&=R_{ref}+E_{ref} \end{aligned} \quad (5)$$

Hereinafter, we use subscript src and ref referring to source face image and reference face image respectively.

2.2. Homomorphic wavelet filtering

It has been theoretically proved by the spherical harmonics analysis that the illumination component $e(x,y)$ in (1) is mainly distributed in the low frequency area of the image $i(x,y)$ [9, 10, 11]. As shown in Fig. 2, in this paper, we estimate E from I using homomorphic wavelet filtering. Wavelet analysis has been widely applied in mathematics and engineering in the last decades. Especially, wavelet basis function supports multiresolution analysis (MRA) [12]. MRA based on wavelet can provide a fine to coarse representation of the input image through different scale independent decomposition. During this decomposition process across different scales, the illumination component of one face image is well preserved while the shape variation against other individuals is largely reduced. Therefore, the approximation coefficients cA in the coarsest scale gives a good approximate of the illumination component E in I. Then a homomorphic filtering procedure is performed to filter out the small amount of illumination component distributed in all the detail coefficients cD. These two

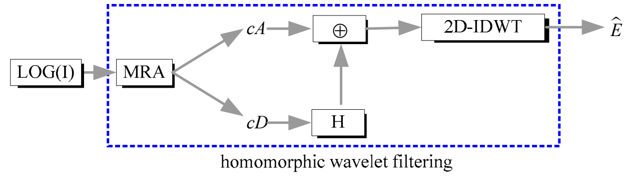

Figure 2: Procedure of homomorphic wavelet filtering

parts are combined together and inverse 2-D discrete wavelet transform (2D-IDWT) is performed to get the final estimate $\widehat{E}$ of the illumination in image I.

We adopt 2-D discrete wavelet to perform 2-D MRA on an image. A 2-D scaling function can be constructed from one-dimensional ones by tensor product [12] and it is defined as below:

$$\begin{aligned} \Phi_{m,n_1,n_2}(t_1,t_2)&=\varphi_{m,n_1}(t_1)\varphi_{m,n_2}(t_2)\\ &=2^{-m}\varphi(2^{-m}t_1-n_1)\varphi(2^{-m}t_2-n_2) \end{aligned} \quad (6)$$

where φ is the 1-D scaling function, m is the scale level, t_1 and t_2 range over the whole image, shifting parameters n_1 and n_2 are integers. Corresponding to the scaling function in Equ. (6), there are three wavelet functions:

$$\begin{aligned} \psi^h_{m,n_1,n_2}(t_1,t_2)_{(t_1,t_2)\in I}&=\varphi_{m,n_1}(t_1)\phi_{m,n_2}(t_2)\\ \psi^v_{m,n_1,n_2}(t_1,t_2)_{(t_1,t_2)\in I}&=\phi_{m,n_1}(t_1)\varphi_{m,n_2}(t_2)\\ \psi^d_{m,n_1,n_2}(t_1,t_2)_{(t_1,t_2)\in I}&=\phi_{m,n_1}(t_1)\phi_{m,n_2}(t_2) \end{aligned} \quad (7)$$

where ϕ is the 1-D wavelet function. And then Equ. (6) and (7) are used to perform MRA on I_{src} and I_{ref} separately. The procedure of MRA on a face image can be intuitively represented as in Fig. 3.

Wavelet-based MRA leads to a decomposition of approximation coefficients (cA_m) at scale level m into four components at level $m+1$: the approximation (cA_{m+1}) and the details in three orientations - horizontal (cD^h_{m+1}), vertical (cD^v_{m+1}) and diagonal (cD^d_{m+1}), which can be computed separately by the inner product of cA_m with scaling and wavelet functions in Equ. (6) and (7) separately:

$$\begin{aligned} cA_{m+1}(t_1,t_2)&=\left\langle cA_m,\Phi_{m,n_1,n_2}(t_1,t_2)\right\rangle\\ cD^h_{m+1}(t_1,t_2)&=\left\langle cA_m,\psi^h_{m,n_1,n_2}(t_1,t_2)\right\rangle\\ cD^v_{m+1}(t_1,t_2)&=\left\langle cA_m,\psi^v_{m,n_1,n_2}(t_1,t_2)\right\rangle\\ cD^d_{m+1}(t_1,t_2)&=\left\langle cA_m,\psi^d_{m,n_1,n_2}(t_1,t_2)\right\rangle \end{aligned} \quad (8)$$

In this paper, we adopt Daubechies wavelets for MRA and a scale level of two or three is found to be suitable in our experiments.

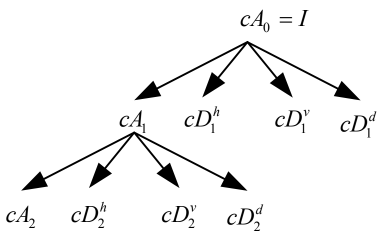

Figure 3: MRA Procedure for image I with two scales.

Through MRA, we get the approximation coefficients cA_n at scale n, which contains almost all the illumination component of I. However, a statistics for the variance of MRA coefficients difference between side and ideal lighting conditions reveals that illumination effects also appear in detail coefficients cD_n (cD_n^h, cD_n^v and cD_n^d), so a further lifting procedure is necessary for getting a more accurate estimate for illumination component, and a homomorphic filtering is employed to separate the illumination component from cD_n in all scale levels. We use a high-pass Butterworth filter [13] as the filter H in Fig. 2. At last, we get the final estimate of E which we denote as $\widehat{E}$:

$$\begin{aligned} \widehat{E}_{src} &= W^{-1}\left(cA_{n,src} + H \cdot cD_{n,src}\right) \\ \widehat{E}_{ref} &= W^{-1}\left(cA_{n,ref} + H \cdot cD_{n,ref}\right) \end{aligned} \tag{9}$$

where W^{-1} is inverse 2-D wavelet transform, $cA_{n,src}$ and $cA_{n,ref}$ are approximation coefficients after a n-scale MRA, $cD_{n,src}$ and $cD_{n,ref}$ are detail coefficients in all the n scales, H is the high-pass Butterworth filter:

$$H(u,v) = \frac{1}{1 + \left[\dfrac{D_0}{D(u,v)}\right]^{2n}} \tag{10}$$

where D_0 is the cutoff amplitude in wavelet domain, $D(u,v) \in cD_n$ is the amplitude at location (u,v), n is the order of filter. We use $D_0 = 0.95$, $n = 2$ as default setting in our experiments. Then according to Equ. (3), the estimation of R can be computed as:

$$\begin{aligned} \widehat{R}_{src} &= I_{src} - \widehat{E}_{src} \\ \widehat{R}_{ref} &= I_{ref} - \widehat{E}_{ref} \end{aligned} \tag{11}$$

2.3. Illumination Mapping and Inverse LOG

After the illumination components of both the source face image and the reference face image are estimated, what we need to do next is to synthesize a virtual source face image by using the illumination component of the reference face image. This can be done directly by substituting E_{ref} for E_{src}. Specifically, we use a mapping function to transfer the illumination component $\widehat{E}_{ref}$ of the reference face image to the source face image and get the illumination transferred LOG face image $\tilde{I}_{src}$:

$$\tilde{I}_{src} = I_{src} - \widehat{E}_{src} + E'_{src} \tag{12}$$

where

$$E'_{src}(x,y) = \widehat{E}_{ref}(\alpha x, \beta y) \tag{13}$$

α is the width proportion between source face image and reference face image and β is the height proportion between source face image and reference face image.

Finally, the illumination transferred face image can be computed by taking an inverse logarithm transform of Equ. (12):

$$\tilde{i}(x,y) = \exp\left(\tilde{I}_{src}\right) \tag{14}$$

2.4. Example results of illumination transfer

In this subsection, illumination transferred results on different databases are presented. Experiments are conducted on $a)$ less challenging face images without shadow in the AR Face Database [14], and $b)$ challenging face images with severe shadow in the Yale Face Database B [15].

Example illumination transferred results on less challenging AR Face Database are shown in Fig. 4 (a). The first column is the source face images; the second column shows the reference face images which cover different persons and different target illumination; the third column displays the results of our illumination transfer method; and the last column gives the ground-truth. It can be noticed that even when there is a large variation in lighting condition and face shape between source face image and reference face image, our illumination transfer technique is still very effective to generate visually satisfying results.

More example illumination transferred results on challenging Yale Face Database B are shown in Fig. 4 (b). It is not difficult to find that severe shadow occurs in face images of Yale Face Database B and this makes illumination transfer a rather challenging problem. However, the illumination transferred results reveal the effectiveness of our approach and the illumination transferred face images are visually acceptable.

3. Application to light-insensitive face recognition

It is not difficult to find that our approach can also be used as an illumination normalization method for illumination invariant face recognition. This can be done

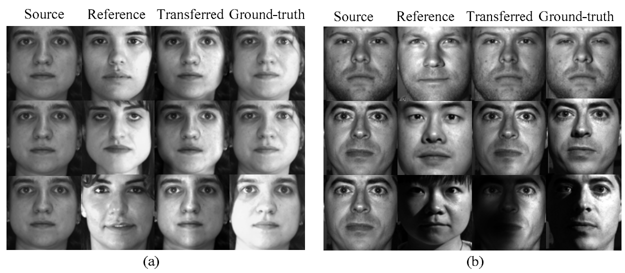

Figure 4: (a) Some illumination transferred results on AR Face Database by using reference images of three different persons under varying lighting conditions. (b) More illumination transferred results on the more challenging Yale Face Database B, which contains severe shadow in face images.

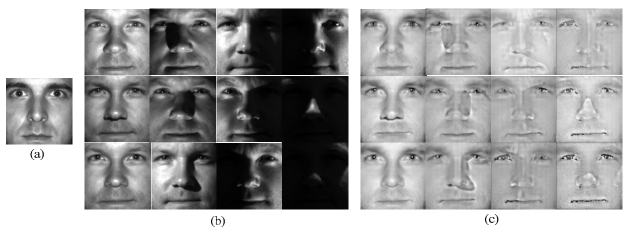

Figure 5: Examples of illumination normalization on Yale Face Database B using our illumination transfer technique.

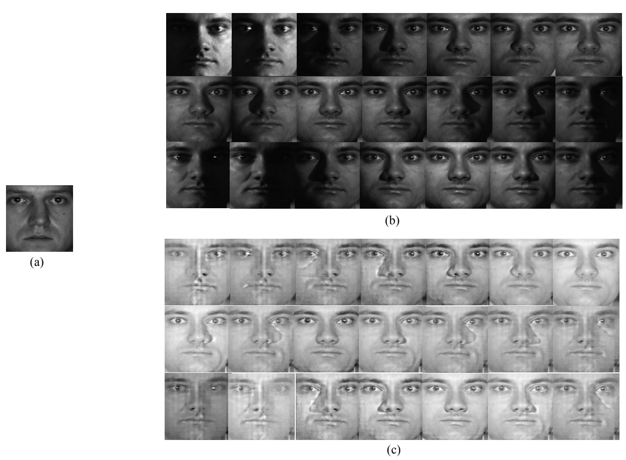

Figure 6: Examples of illumination normalization on CMU PIE Face Database using our illumination transfer technique.

by transferring the illumination of a pre-selected face image with ideal lighting condition to all the face images. In this section, experiments are conducted on Yale face database B [15] and CMU PIE database [16] to show how the proposed method can improve the accuracy of the Eigenfaces face recognition method when complicated lighting conditions are presented.

Note that in our experiments, all the face images are cropped and normalized to the size of 128×128 in accordance with [17].

3.1. Effects of illumination normalization

Some examples of illumination normalization by using the proposed illumination transfer technique are shown in Fig. 5 and Fig. 6 respectively for images in Yale Face Database B and CMU PIE Face Database. In both of the figures, sub-figure (a) shows the reference face image , sub-figure (b) shows the original input face images and sub-figure (c) illustrates the corresponding normalized face images respectively. Clearly, the illumination normalized face images are very uniform, since they are re-lighted by the same reference illumination. Thus, higher recognition accuracy can be expected based on these normalized face images.

3.2. Experiments on face recognition

In this subsection, experimental results are given to show how the proposed illumination transfer technique can facilitate face recognition under complicated lighting conditions. Comparison experiments with some existing illumination normalization algorithms [18, 19] as well as Histogram Equalization (HE) and Logarithm (LOG) transform are conducted on Yale Face Database B [15] and CMU PIE Face Database [16].

Yale Face Database B has been the de facto standard for studies of variable lighting over the past decade [20]. There are ten individuals with 64 different lighting conditions and 9 different poses in Yale Face Database B. Since we only care about the illumination variation, frontal images with 64 different lighting conditions are used in our experiments. All the images are divided into five subsets according to [17] and subset 1 is used as our training set, the other four subsets are used for testing.

CMU PIE is another face database that is frequently used in the studies of illumination invariant face recognition. There are 68 subjects with pose, illumination and expression variations. Also, frontal face images of 68 individuals with 21 different lighting conditions are used in our experiments. As before, the images with the most neutral lighting condition for each individual are used as gallery set and the rest are used as probes.

In our experiments, Eigenfaces [21] with nearest neighbor classifier based on the Euclidean distance is selected as the face recognition method. The comparison results with several existing methods are shown in Table 1. It is worth pointing out that the results of QIR and SQI in the table are taken directly from [2] and [18] respectively. This comparison is reasonable since we have used the same experimental setting. From these results, one can clearly see that the proposed method leads to better accuracy when recognizing faces under complicated lightings conditions.

Table 1: Recognition rate comparison of different illumination normalization methods on Yale B and CMU PIE Face Database.

Methods	Recognition rate(%)				
	Yale B				CMU PIE (1360)
	Subset 2 (118)	Subset 3 (118)	Subset 4 (138)	Subset 5 (189)	
Non	100	88.1	49.3	20.1	43.0
HE	100	89.0	55.1	44.4	47.8
LOG	100	85.6	58.0	69.3	57.0
QIR*	100	100	90.6	82.5	n/a
SQI*	100	95.8	96.4	94.7	95.8
Our method	100	100	97.1	96.8	97.4

*Note: the results in these two rows are directly from [2] and [18] respectively.

4. Conclusion

We propose a novel image processing based approach to transfer the dominant illumination condition of a reference face image to a source face image, without using any prior information of 3-D geometry or lighting condition of face images, which are indispensable for 3D geometry model based methods. There are three main contributions in our approach: first, it is a simple but efficient image processing based method and its results are visually satisfying; secondly, our approach does not rely on any pre-computed reflection map or training set; thirdly, our approach can also be used as an illumination normalization method for illumination invariant face recognition.

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