Fast Retinex Method Based on CMSB-plane for Variable Lighting Face Recognition

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Abstract: In this paper, we propose a fast Retinex method based on CMSB-plane for variable lighting face recognition. Cast shadow, created by direct light sources, seriously damage face images and ultimately deteriorate the performance of face recognition system. To eliminate cast shadow efficiently in the framework of Retinex theory, they should be preserved in the illumination estimation process. The proposed method estimates the illumination with cast shadow by iteratively convolving the input image with a 3Ｘ3 averaging mask adaptively weighted by coefficients based on both the combined most significant bit-plane (CMSB-plane) and image entropy. To improve the performance of the smoothing process, the proposed method employs the multigrid method and combines multi-copies of the estimated illumination with various scales. In this way, we can achieve a fast illumination normalization in which even face images with cast shadow are normalized efficiently. The proposed method has been evaluated based on the CMU PIE database by using PCA. In result, the proposed method has higher recognition rates than other conventional illumination normalization methods such as SSR, MSR and SQI.

1. Introduction

The illumination is the most significant factor which deteriorates the performance of face recognition in variable lighting conditions. To solve illumination problem for face recognition, variety methods are developed over decade years. Especially, illumination normalization methods based on Retinex theory [1] are very attractive because of simplicity and efficiency.

We propose fast and robust illumination normalization method for face recognition in variable lighting conditions. The proposed method is based on Retinex theory [1] because it can normalize the illumination from single input image effectively. There are two basic assumptions for illumination normalization in Retinex theory. One is that an image $I(x, y)$ is regarded as the product $I(x, y)=R(x, y)L(x, y)$ where $R(x,y)$ is the reflectance and $L(x,y)$ is the illumination at each pixel (x, y). Therefore, illumination normalization can be achieved by dividing the illumination from the input image. And the other is that the variation of the illumination is smaller than that of the reflectance, that is, the illumination generally occupies lower frequency region in frequency domain. Therefore, estimation of the illumination using low-pass filter (e.g. averaging filter in spatial domain) is very important step for illumination normalization. To estimate the illumination well beyond the simple low-pass filtering, we propose the novel adaptive smoothing.

Advantages of the proposed method are as follows. First, the proposed method uses combined most significant bit-plane (CMSB-plane). By using CMSB-plane, the proposed method estimates the illumination even with shadow discontinuities well. Second, multigrid method [2] is employed to improve the computational efficiency of the estimation process. By using this method in the framework of the adaptive smoothing, the required number of iteration for illumination estimation is reduced. Third, inspired by the idea of multi-scale Retinex (MSR) [3], the proposed method combines multi-copies of the estimated illumination which are taken at various iteration steps. By this way, both dynamic range compression and tonal rendition can be achieved simultaneously. And the proposed method has been evaluated based on CMU PIE database [4] by using Principle Component Analysis (PCA) for face recognition.

The rest of the paper is organized as follows: Section 2 reviews the Retinex theory for illumination normalization and describes the analytic evaluation of the proposed method. Section 3 represents the experimental results of recognition rates. Finally, conclusions are offered, along with some discussions, in section 4.

2. Illumination Estimation/Normalization

In general, Retinex theory has the basic assumption that the variation of the illumination is smaller than the variation of the reflectance which corresponds to facial feature. By this assumption, the illumination can be estimated just by smoothing the input face image. However, cast shadow violates this basic assumption, and they still remain even after the illumination normalization as shown in figure 1.

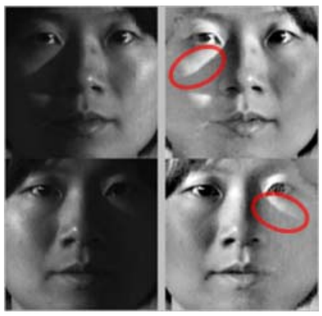

Figure 1. Original image (left) and illumination normalized image (right) by single-scale Retinex (SSR)

To remove cast shadow, the discontinuities of them should be preserved in the illumination estimation process. If cast shadow is well preserved in the estimated illumination, the illumination would be normalized efficiently by dividing the estimated illumination into the original image by Retinex theory. The general framework of Retinex theory is shown in figure 2.

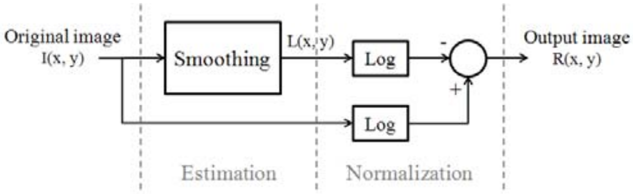

Figure 2. General framework of Retinex theory

2. 1 Combined Most Significant Bit (CMSB)-plane

In Retinex theory, the main issue is how correctly the illumination is estimated to normalize the illumination with shadow discontinuities. For this purpose, we use the bit-planes of face image. Figure 3 shows the original face image with shadow discontinuities and its bit-planes.

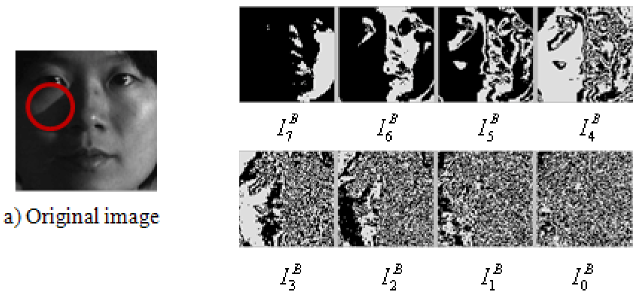

Figure 3. Bit-planes of a face image

As shown in the figure 3, bit-planes $I_h^B\ (0 \le h \le 7)$ have some useful characteristics. First, the most significant bit-planes contain most of shadow discontinuities. Second, the least significant bit-planes have the less important information of face than most significant bit planes.

To facilitate the measurement of shadow discontinuities, the proposed method uses the combined most significant bit (CMSB)-plane which is constructed by some most significant bit-planes. As the input face image I is given, the CMSB-plane can be determined as follows.

$$BP_c(x,y) = I_c^B(x,y) \oplus I_{c+1}^B(x,y) \oplus \cdots \oplus I_7^B(x,y) \quad 3 \le c \le 7 \quad (1)$$

Here, $\oplus$ denotes bit-wise logical OR operation. As you can see in the figure 4, the CMSB-plane of input face image has the same intensity values in the homogeneous region like cast shadow region, but this region has different intensity values before CMSB-plane processing.

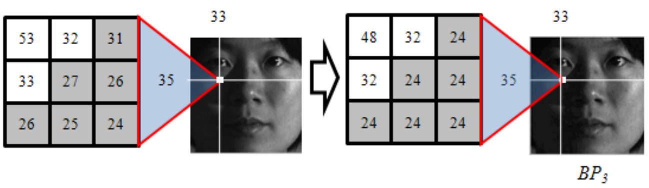

Figure 4. Intensity values of original face image and CMSB-plane

After all, by using the CMSB-plane, we can determine the shadow discontinuities just based on intensity value of each pixel, and construct the adaptive smoothing mask for estimating the illumination.

2. 2 Adaptive Smoothing Mask

The adaptive smoothing mask $M_{x,y}$ with 3 X 3 size at each pixel *(x, y)* of input face image I is given as follows.

$$M_{x,y}(i,j) = \begin{cases} 1, & if\ \ BP_c(x+i, y+j) == BP_c(x,y) \\ \alpha_{x,y}, & otherwise \end{cases} \quad (2)$$

where $\alpha_{x,y}$ $(0 \le \alpha_{x,y} \le 1)$ is a coefficient of smoothing mask at each pixel *(x,y)*. To assign the coefficients adaptively, we employ the image local entropy which represents the amount of image information at each 3 X 3 region. Image local entropy of 3 X 3 region at each pixel *(x,y)* can be calculated as follows.

$$\varepsilon_{x,y} = -\sum_{i=-1}^{1}\sum_{j=-1}^{1} p_{x,y}(i,j)\log_2 p_{x,y}(i,j) \qquad 1 \le x \le M,\ 1 \le y \le N$$

with

$$p_{x,y}(i,j) = \frac{n_k}{9} \quad (3)$$

where $p_{x,y}$ is local histogram in 3 X 3 mask of face image, and n_k is the number of pixels with value k in 3 X 3 mask. Figure 5 presents the face images which has cast shadow caused by left/right light sources and local entropy image of the face images.

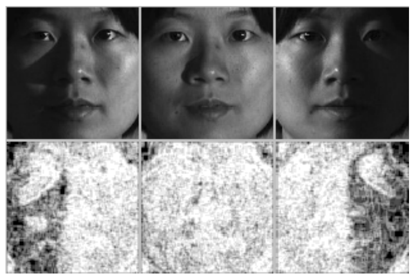

Figure 5. Face images with cast shadow and local entropy of the images

As shown figure 5, the amount of the information decreases in region of cast shadow. Therefore, to preserve the information in 3 X 3 masks, we assign the coefficients of the mask $M_{x,y}$ adaptively as follows.

$$\alpha_{x,y} = 1 / (1 + \varepsilon_{x,y})^2 \quad (4)$$

Therefore, as $\varepsilon_{x,y}$ is close to '0', $\alpha_{x,y}$ is close to '1'. Effect of $\alpha_{x,y}$ value based on entropy can be explained by the constructed smoothing mask $M_{x,y}$ on the shadow discontinuity region.

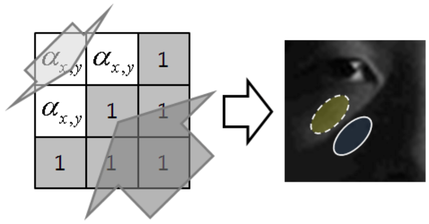

Figure 6. Smoothing effect of adaptive smoothing mask on cast shadow

As shown in the figure 6, the constructed smoothing mask has the characteristic of preserving shadow discontinuities. If $\alpha_{x,y}$ is close to '1', then this mask is just the averaging filter without preserving the shadow discontinuities. On the other hands, if $\alpha_{x,y}$ is close to the '0' on the discontinuity region, then smoothing mask operates like figure 6.

2. 3 Multigrid Method

The proposed method is mainly based on the iterative convolution to convolve 3 X 3 smoothing mask, in which an efficient short-length convolution is performed to build a long convolution. Then, multigrid method is the fast iterative convolution method.

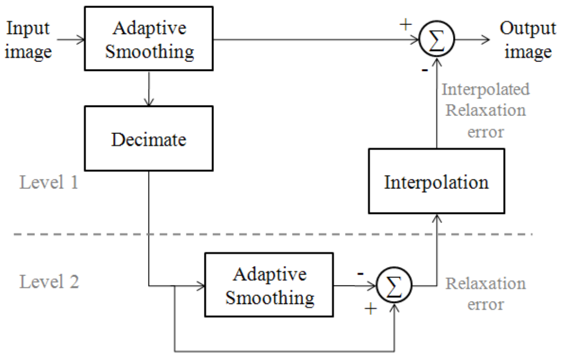

Figure 7. Block diagram of multigrid method

As shown in figure 7, in level 1, multigrid method iteratively convolves the face image by the smoothing mask to relax the input image with original image size. And then, after the result of level 1 is down sampled, relaxation is performed once more in level 2.

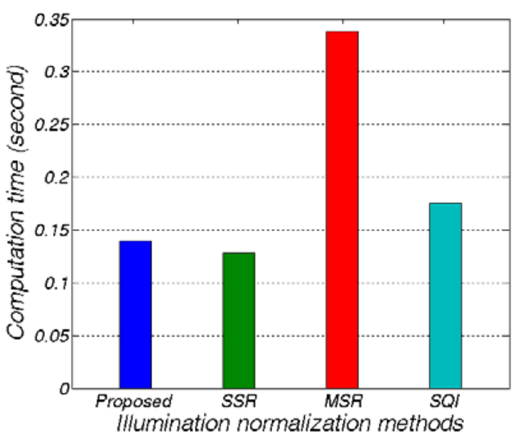

Figure 8. Computation time of each method

In this process, the computation time can be improved notably because the relaxation is performed to just half size image in level 2. The difference caused by using the half size image is conpensated to the result of level 1 with original size through interpolation.

Figure 8 shows the computation time of each illumination normalization method which is performed to one face image with 100 X 100 size.

2. 4 Illumination Normalization

In this section, we present illumination normalization of the proposed method. In general, Retinex theory has trade-off between dynamic range compression and tonal rendition. Therefore, we employ the idea of multi-scale Retinex (MSR) to achieve both dynamic range compression and tonal rendition. The main idea of MSR is to combine multi-copies of the illumination estimated by convolving an input face image with kernels of various sizes. In the proposed method, this idea can be implemented efficiently because multi-copies of the estimated illumination, in the course of just one iterative convolution, can be taken. Figure 9 shows illumination normalization of the proposed method.

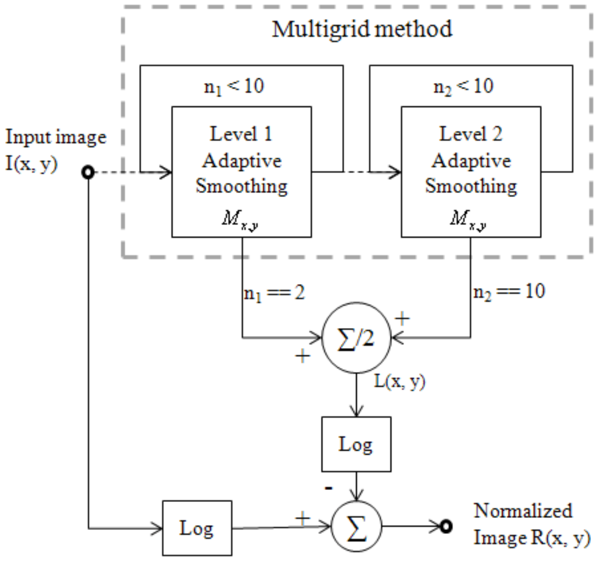

Figure 9. Illumination normalization of the proposed method

3. Experimental Result

In this section, to verify the efficiency of the proposed method, we firstly check normalized results of some face images visually and then evaluate the recognition rate of face images preprocessed by the proposed method and other methods such as SSR [5], MSR and SQI [6]. In order to evaluate the proposed method, we use the images from CMU PIE database.

3. 1 CMU PIE Database

The CMU PIE database [4] contains 41,368 images obtained from 68 subjects. We took the frontal face images with 21 different illumination conditions which are captured without room lights. Thus, the total number of images we used for our test is 1,428.

3. 2 Comparison of Normalization results

Figure 10 shows the illumination normalization results of one subject in CMU PIE database. To validate our proposed method, we chose two images which have cast shadow.

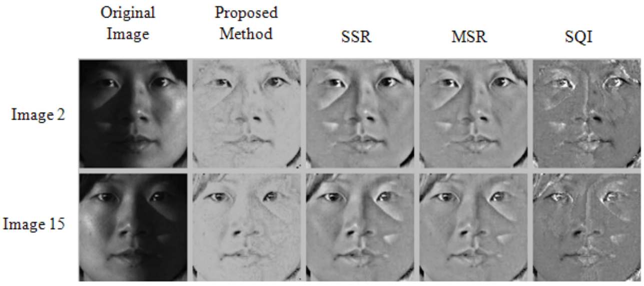

Figure 10. Comparison of illumination normalization results

As shown in figure 10, cast shadows are effectively eliminated for the proposed method, but they are still remained in results of other methods.

Figure 11. 21 different illumination conditions for a subject in CMU PIE database and their illumination normalization results by the proposed method

Figure 11 shows the illumination normalization results of one subject in CMU PIE database. Note that the proposed method has good results even when images with bad illumination conditions (1, 2, 15 and 16th image) are used as a training set.

3. 3 Recognition rate

The recognition rates were computed using the k-fold strategy by PCA algorithm: i.e. k images of each subject (in our test, k = 1) are selected for training and the remaining 21 – k images of each subject are selected for test. Figure 12 shows the recognition rates for each trial.

The proposed method outperforms other methods in terms of the recognition rate and has the averaging recognition rate of 98.5854%. Especially, the proposed method has good results even when images with bad illumination conditions (1, 2, 15 and 16th image) are used as a training set.

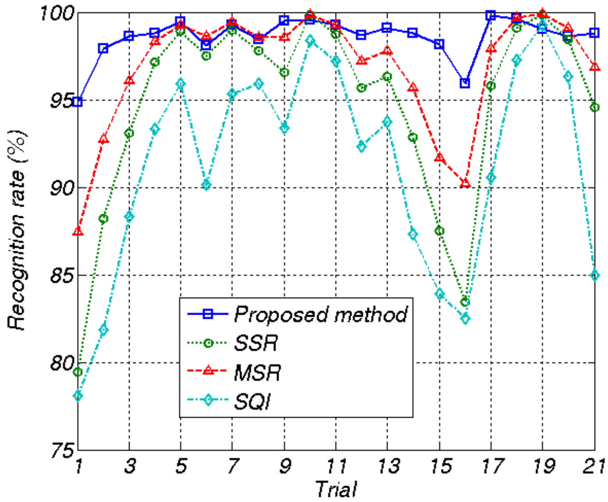

Figure 12. Recognition rates (%) on CMU PIE database

4. Conclusion

In this paper, we proposed a fast Retinex method for variable lighting face recognition. In general framework of Retinex theory, adaptive smoothing, which convolves an input image iteratively with a 3 X 3 smoothing mask, and multigrid method were employed for the fast illumination estimation. Using the proposed method, we showed that images with even strong cast shadow can be effectively normalized. And the performance of the recognition accuracy in face recognition was better than other methods. We believe that the proposed method has a wide range of applications in face recognition systems in variable lighting conditions.

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