Illumination Compensation for Face Image using Retinex Method Based on Bilateral Filtering

Dawei Yang
State Key Laboratory of Robotics, Shenyang Institute of Automation, Chinese Academy of Science, Shenyang 110016, China
Graduate University of the Chinese Academy of Science, Beijing 100049, China
Shenyang Ligong University, Shenyang 110159, China
dwyang@sia.cn:

Yandong Tang
State Key Laboratory of Robotics, Shenyang Institute of Automation, Chinese Academy of Science, Shenyang 110016, China
ytang@sia.cn

***Abstract*— Illumination variation is one of the critical factors affecting face recognition rate. In the paper, we propose a novel Retinex method based on bilateral filtering to compensate the illumination for face image. The proposed method estimates the illumination using the bilateral filtering, and applies the Retinex theory to obtain the reflectance image which is illumination invariant. The experimental results validate the performance of the method.**

Keywords-Illumination compensation; Retinex method; Bilateral filtering; Face image

I. INTRODUCTION

Face recognition has many advantages, such as non-intrusion, free-contact, cover-up, etc, compared with fingerprint recognition and iris recognition. However, there are some difficult problems on face recognition. The illumination variation is almost always greater than the identity variations in face images [1]. For example, ambient lighting is quite different during the course of a day, and from one day to another, as well as between indoor and outdoor environments. Moreover, strong shadows cast from a direct source can make facial features invisible.

Many methods have been proposed to solve the problems of the varying illumination of faces images. In the feature-based approaches, faces are represented by illumination invariant features. Typically these are geometrical measurements and relationships between local facial features such as the eyes, mouths, noses and chins [2]. The feature-based methods are known to be robust against varying illumination conditions. However, they rely on the accurate face and facial feature detection. In holistic methods, the entire face image (image pixel values) is considered for face representation without taking into account any specific geometrical features. A face image could be thought of as a point in a high dimensional image space. To avoid computational complexities and to reduce redundant data, face images are first linearly transformed into a low dimensional subspace before extracting a feature vector. The most commonly used dimension reduction technique is the Principal Component Analysis (PCA), also known as Karhunen-Love transform (KLT) [3]. PCA is known to retain within-class variations due to illumination and pose. However, it has been demonstrated that leaving out the first 3 eigenfaces (that corresponds to the 3 largest eigenvalues) could reduce the effect of variations in illumination [4]. However, it may also lead to the loss of the information useful for accurate identification. The generative methods [5-7] have been utilized to address the problem of varying illumination conditions in face recognition based on the assumption of the Lambertian model. The previous work demonstrates that the variability of images under a fixed pose, consisting of only diffuse reflection components and varying illumination conditions can be represented by a linear combination of three basis images [8]. Belhumeur and Kriegman [9] demonstrate that a set of images of an object under fixed posed, consisting of diffuse reflection components and shadows under arbitrary lighting conditions forms a convex cone, termed the illumination cone, in the image space and that this illumination cone can be approximated by a low-dimensional subspace. These generative methods perform well under varying illumination conditions, but they require a number of training samples which represent extreme illumination conditions. It may be possible to acquire a number of training images in the certain applications such as ID cards and drivers license, but difficult to get those in the surveillance and the counter terrorism related applications.

Recently, the methods based on Retinex theory have been applied to the illumination compensation. The theoretic foundation of the Retinex theory [10] is that an image $I(x, y)$ is regarded as the product $I(x, y) = L(x, y) * R(x, y)$, where $R(x, y)$ is the reflectance and $L(x, y)$ is the illumination. The nature of $L(x, y)$ is determined by the illumination source, whereas $R(x, y)$ is determined by the characteristics of the imaged objects. Therefore, the illumination normalized images for face recognition can be achieved by estimating the illumination L and then dividing the image I by it. There is a common assumption that the edges in the scene are edges in the reflectance, while the illumination spatially changes slowly in the scene. Thus, in the most Retinex methods, the reflectance R is estimated as the ratio of the image I and its smooth version which serves as the estimate of the illumination L. Single Scale Retinex

978-0-7695-4249-2/10 $26.00 © 2010 IEEE
DOI 10.1109/ICINIS.2010.38

(SSR) [11], employes a simple linear filter with Gaussian kernel. However, strong shadow cast from a direct light source violates the assumption that the illumination varies slowly, and halo effects are often visible at large illumination discontinuities in I. Multiscale Retinex (MSR) [12] decomposes an image into pyramid images, and then synthesize them to get the reflectance image. These Retinex methods have the common advantages: They don't require training images and have relatively low computational complexity. However, these methods still cannot completely remove the cast shadows. To solve these problems, an efficient discontinuity preserving filter must be employed to estimate L.

In this paper, we present a novel Retinex method based on bilateral filtering [11] to compensate the illumination for face image. Our method preserves the discontinuity of the illumination image by bilateral filtering and then obtains accurate illumination invariant image. The paper is organized as follows. In Section II, we review the general framework of Retinex and bilateral filtering, and then introduce the proposed method. In Section III, the experiments on the face images taken outdoors and indoors are done, followed by the analysis of the experimental results. Section V is the conclusion.

II. THE RETINEX METHOD BASED ON THE BILATERAL FILTERING

In this section, we review the general framework of Retinex method and the bilateral filtering, and then describe the proposed method.

A. *the Retinex Method*

Retinex theory deals with compensation for illumination effects in images. The primary goal is to decompose a given images S into two different images, the reflectance image R, and the illumination image L. Illumination L is estimated as a smooth version of input image I as discussed last section. In fact, there are cast shadows in face image and it will violate the assumption that the illumination varies slowly. This implies that the estimated illumination must be discontinuities of intensity [14]. Once the estimation is completed, illumination is normalized by taking the difference between the logarithms of the input image and the estimated illumination. The logarithmic function removes noise from the image and makes it possible to promote useful signals more.

The first step taken by most algorithms is the converion to the logarithmic domain by $s = \log S$, $l = \log L$, $r = \log R$, and thereby $s = l + r$. This step is motivated both mathematically, preferring additions over multiplications, and physiologically, referring to the sensitivity of our visual system. The different Retinex algorithms usually have the same flow chart as shown in Figure 1, and the difference between them concentrates on the actual estimation of the illumination images. In this framework, the estimation of illumination is the core procedure so the proper smoothing method must be carefully selected, and we select the bilateral filtering.

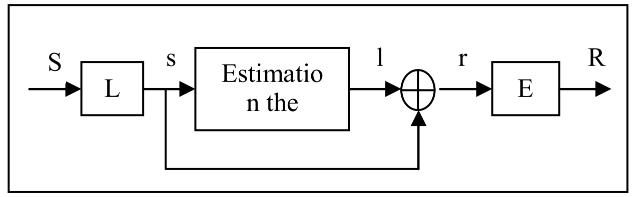


Figure 1. The general flow chart of Retinex algorithms

B. *Bilateral Filtering*

A bilateral filter is an edge-preserving smoothing filter. Whereas many filters are convolutions in the image domain, a bilateral filter also operates in the image's range—pixel values. Rather than simply replacing a pixel's value with a weighted average of its neighbors, as for instance the Gaussian filter does, the bilateral filter replaces a pixel's value by a weighted average of its neighbors in both space and range (pixel value). This preserves sharp edges by systematically excluding pixels across discontinuities from consideration.

Bilateral Filtering can be described as follows:

$$h(x) = k^{-1}(x) \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(\xi)c(\xi,x)s\big(f(\xi),f(x)\big)d\xi \quad (1)$$

with the normalization

$$k(x) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} c(\xi,x)s\big(f(\xi),f(x)\big)d\xi \quad (2)$$

where $c(\xi,x)$ measures the geometric closeness between the neighborhood center x and a nearby pixel ξ. $s\big(f(\xi),f(x)\big)$ measures the photometric similarity between the pixel at the neighborhood center x and that of nearby point ξ

C. *the Proposed Method*

Based on the theories discussed above, we proposed a novel Retinex Method Based on Bilateral Flitering. A shift-invariant Gaussian filtering is chosen to estimate the illumination L, in which both the closeness function c and the similarity function s are Gaussian function of the Euclidean distance between their arguments.

$$c(\xi,x) = e^{-\frac{1}{2}\left(\frac{d(\xi,x)}{\sigma_d}\right)^2} \quad (3)$$

where

$$d(\xi,x) = d(\xi - x) = \|\xi - x\| \quad (4)$$

is the Euclidean distance between ξ and x. The similarity function s is as follows:

$$s(\xi,x) = e^{-\frac{1}{2}\left(\frac{d(f(\xi),f(x))}{\sigma_r}\right)^2} \quad (5)$$

Where

$$d\big(f(\xi),f(x)\big) = s\big(f(\xi) - f(x)\big) = \|f(\xi) - f(x)\| \quad (6)$$

is a measure of distance between the two intensity values $f(\xi)$ and $f(x)$.

The geometric spread σ_d in the domain is chosen based on the desired amount of low-pass filtering. The photometric spread σ_r in the image range is set to achieve the desired amount of combination of pixel values.

By taking the difference between the logarithms of the input image I and the estimate illumination L, we can get the reflectance image R'. The procedure can be formulated as follows:

$$R'(x,y) = \log(I(x,y) + 1) - \log(L(x,y) + 1) \quad (7)$$

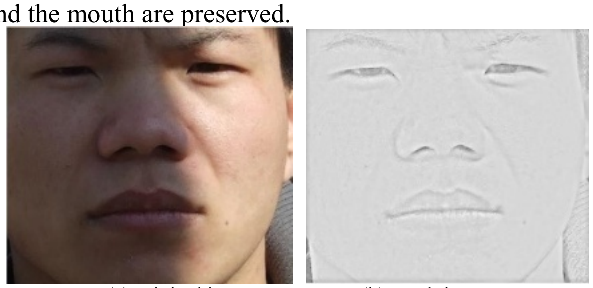
According the assumption of the Retinex theory, the reflectance R is restricted to be in the range $R \in [0,1]$, and $L \geq S$, so the output R'(x,y) is always negative. Therefore, we normalize R'(x,y) into the range [0,1] by

$$R(x,y) = \frac{R'(x,y) - R'_{min}}{R'_{max} - R'_{min}} \quad (8)$$

Where R'_{min} and R'_{max} are the minimal and maximal values of $R'(x,y)$ across the whole image.

III. EXPERIMENTAL RESULTS

In this section we show the experimental results of the proposed method and the comparisons with the MSR method. Figure 2(a) is an image taken outdoors, in which half of the face is shad with the shadow. The image in Figure 2(b) is the output of the proposed method. The values of the parameters σ_d and σ_r are 10 and 100 respectively. The shadow of the original image has been removed but the main features, such as the eyes, the nose, and the mouth are preserved.

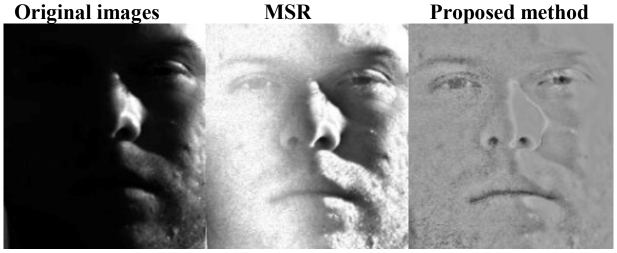


(a) original image (b) result image

Figure 2. The output image of the proposed method

Figure 3 shows the comparison between the results by the proposed method and the those by the MSR method. The images in the first column are selected from the Yale B database. They are taken indoors in different illumination conditions. The shades on their face are so serious that some features are invisible, such as the eyes and the eyebrow. The images in the middle column are the results by the MSR method; those in the right column are the ones by the proposed method. Although the MSR method can compensate the illumination, it relates to the iterative pyramid decompose and synthesize, and the amounts of computation are complex. The proposed method removes the shadow well, and the implement is simple. Once selecting the appropriate parameters, we can get better results. The average recognition rates are also computed as shown in Table 1.

Original images **MSR** **Proposed method**



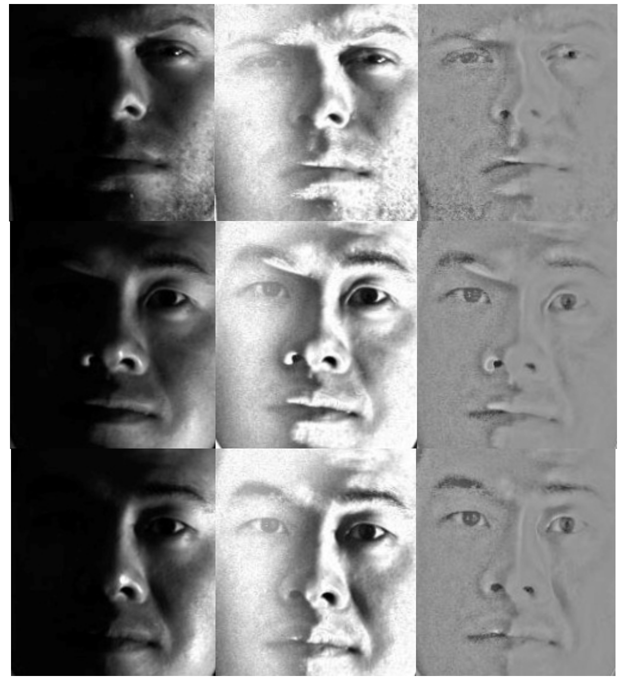


Figure 3. The comparison with MSR

Table 1 Average recognition rate comparison

	The Proposed method	*MSR*
Average recognition rate(%)	98.91	97.43

IV. CONCLUSION

In this paper, we propose a novel Retinex method based on bilateral filtering for the illumination compensation of face images. According to the Retinex theory, an image consists of illumination and reflectance. Smoothing filters have been the methods to estimate the illumination. Bilateral filtering can preserves the discontinuity which compensates the disadvantage of the Retinex-based method. We test the proposed method on the images outdoors and indoors, and compare it with the MSR. The comparison between the average recognition rates of the MSR and that of ours validate the higher performance of the proposed method.

In our method, we select shift-invariant Gaussian filtering to estimate the illumination. The estimation results are affected by the parameters of the bilateral filter. In future, how to choose appropriate parameters is our investigation goal. The future work: Studying the relation between the effect of illumination compensation and the selection of the parameters; exploring the method to extracting the illumination invariant features.

REFERENCES

[1] Adini, Y., Moses, Y., Ullman, S., Face recognition: The problem of compensating for changes in illumination direction. IEEE Trans. Pattern Anal. Machine Intell. vol. 19, 1997, ppt. 721-732.

[2] R. Brunelli and T. Poggio, "Face Recognition: Feature vs. Templates, "IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 15(10), pp. 1042-1053, October 1993.

[3] M. Turk and A. Pentland, "Eigenfaces for Recognition," Journal of

Cognitive Neuroscience, vol. 3(1), pp. 71-86, 1991.

[4] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 19(7), pp. 711-720, July 1997.

[5] A. S. Georghiades, P. N. Belhumeur, and D. J. Kriegman, "From few to many: Illumination cone models for face recognition under variable lighting and pose," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 23(6), pp. 643-660, June 2001.

[6] T. Okabe and Y Sato, "Object recognition based on photometric alignment using RANSAC," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, vol. 1, pp. 221-228, June 2003.

[7] K-C. Lee, J. Ho, and D. J. Kriegman, "Acquiring Linear Subspaces for Face Recognition under Variable Lighting," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 27(5), pp. 684-698, May 2005.

[8] A. Shashua, "On Photometric Issues in 3D Visual Recognition from a Single 2D Image," International Journal of Computer Vision, vol. 21(1-2), pp. 99-122, January 1997.

[9] P. N. Belhumeur and D. J. Kriegman, "What is the set of images of an object under all possible lighting conditions?," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 270-277, 1996.

[10] R. Gross, V. Brajovic, An image preprocessing algorithm for illumination invariant face recognition, in: Fourth International Conference on Audio and Video Based Biometric Person Authentication, 2003, pp. 10-18.

[11] D.J. Jobson, Z. Rahman, G.A. Woodell, Properties and performance of a center/surround Retinex, IEEE Trans. Image Process. 6(3) (1997) 451-462.

[12] D.J. Jobson, Z. Rahman, G.A. Woodell, A multiscale Retinex for bridging the gap between color images and the human observation of scenes, IEEE Trans. Image Process. 6(7) (1997) 965-976.

[13] C. Tomasi, R. Manduchi, Bilateral filtering for gray and clolr images, in: Proceedings of the 1998 IEEE International Conference on Computer Vision, Bombay, India, 1998.

[14] D. Shaked, R. Keshet, Robust recursive envelope operators for fast Retinex, Hewlett-Packard Research Laboratories Technical Report HPL-2002-74R1,2002.