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AN EFFECTIVE ILLUMINATION COMPENSATION METHOD FOR FACE RECOGNITION

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Key words: face recognize, illumination compensation, anisotropic smoothing, homomorphic filtering.

ABSTRACT

Face recognition is very useful in many applications, such as safety and surveillance, intelligent robot, and computer login. The reliability and accuracy of such systems will be influenced by the variation of background illumination. Therefore, how to accomplish an effective illumination compensation method for human face image is a key technology for face recognition. Our study uses several computer vision techniques to develop an illumination compensation algorithm to processing the single channel (such as grey level or illumination intensity) face image. The proposed method mainly consists of three processing modules: (1) Homomorphic Filtering, (2) Ratio Image Generation, and (3) Anisotropic Smoothing. Experiments have shown that by applying the proposed method the human face images can be further recognized by conventional classifiers with high recognition accuracy.

I. INTRODUCTION

In recent years, digital video signal processing is very popular because digital audio and video technology have made a lot of progress, the price of large data storage is lower and the cost of the optical photographic equipments also decreases. Most importantly, artificial intelligence and computer vision technology are getting mature. So intelligent video processing systems gain much attention to the public, especially it has become a very important role in the safety monitoring field. In this field, the accuracy of face recognition is an essential goal to pursue, so we address this issue here, and hope to be able to develop a high accuracy of face recognition.

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For face recognition, there are several problems which will affect the recognition accuracy. Among them, ambient lighting variation is a very crucial problem because it will affect the system performance considerably. Currently, most face recognition methods assume that human face images are taken under uniform illumination, but in fact the background illumination is usually non-uniform and even unstable. Therefore, the face images of the same person often have very different appearances which make face recognition very difficult. Furthermore, slanted illumination probably produces different shadows on face images which may reduce the recognition rate greatly. So this research focuses on this topic and proposes an illumination compensation method to improve the recognition accuracy under different background illumination.

There are many approaches have been proposed already, such as Retinex [10], Illumination Cone [2], Quotient Image [12], Self-Quotient Image [15], Intrinsic Illumination Subspace [4], Columnwise linear Transformation [8], Logarithmic Total Variation model [5] , Discrete Cosine Transform [6] algorithm and Gradient faces [16] method. Retinex is an algorithm to simulate human vision which main concept is the perception of the human eye will be affected by the object reflectance spectra and the surrounding lighting source. Therefore, in order to get the ideal image it computes each pixel's albedo by subtracting the intensity of this pixel and those of its surrounding eight pixels, which results in the original Retinex algorithm, also called Single Scale Retinex, SSR. In recent years, several algorithms based on this concept but using more neighboring pixels also were proposed and they proclaimed to produce better performance than Retinex, just like Multi-Scale Retinex, MSR [9] and Multi-Scale Retinex with Color Restoration, MSRCR [9]; Illumination Cone constructs a specific three-dimensional facial model for each person, then various illuminated two-dimensional images of one person can be constructed from his own three-dimensional facial model. All of Quotient Image, Self-Quotient Image and Intrinsic Illumination Subspace adopt an image preprocessing. Quotient Image (QI) has to input at least three images under different background illumination in order to remove the information of lighting source. Self-

Quotient Image (SQI) is derived from Quotient Image and it needs only one input image to perform lighting compensation. Therefore, it is easily applied to all kinds of recognition systems. Being similar to QI and SQI, Intrinsic Illumination Subspace first uses a Gaussian Smoothing Kernel to obtain the smoothed image, and then it reconstructs an image with the basis of the intrinsic illumination subspace. Columnwise linear Transformation assumes that by accumulating each column of each human face image the intensity distributions of different persons are very similar. So, the average intensity distribution A nontrivial is computed from all the training face images first, and the intensity distribution B of the current processed face image is also computed, then by transforming B to A, a compensated face image can be derived. The Logarithmic Total Variation (LTV) model is derived from the TV-L^1 model [3] and the TV-L^1 model is particularly suited for separating "large-scale" (like skin area) and "small-scale" (like eyes, mouth and nose) facial components. So the LTV model is also retain the same property. The Discrete Cosine Transform (DCT) algorithm transforms the input image from spatial domain to frequency domain first. Finally, Gradient faces method use Gaussian kernel function to transform the input image to gradient domain and get the Gradient faces to recognition.

However, these methods still have their shortcomings and deficiencies. For example, both Illumination Cone and Quotient Image require several face images of different lighting directions in order to train their database; all of Retinex, Self-Quotient Image, Intrinsic Illumination Subspace, Columnwise linear Transformation, LTV model, DCT algorithm and Gradient faces method cannot tolerate the face angle deviation and certain coverings (such as sunglasses) on faces. For the above reasons, our approach references the previous approaches to propose a novel illumination compensation method. The proposed method is based on "combination" and "complementarity" two key ideas to combine three distinct illumination compensation methods. It can efficiently eliminate the effect of background lighting change, so a subsequent recognition system can accurately identify human face images under different background illumination.

This paper is arranged into 4 sections. Section 2 describes the concept and the processing steps of the proposed compensation algorithm; Section 3 describes the testing database and experimental results; finally, conclusion is drawn in Section 4.

II. THE PROPOSED ILLUMINATION COMPENSATION METHOD

In order to eliminate the effect of background lighting, we assume that (x, y) is the coordinate of an image pixel $\boldsymbol{P}$, $f(x, y)$ is the gray value of P. So based on a Lambertian model [12], $f(x, y)$ can be expressed by the multiplication of two functions [2, 11, 12], which is

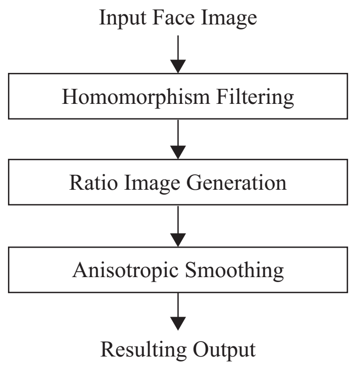

Fig. 1. The processing diagram of the proposed method.

$$f(x, y) = i(x, y)r(x, y). \tag{1}$$

In this function, $i(x, y)$ is the illuminance of $\boldsymbol{P}$ and $r(x, y)$ is the reflectance of P. In general, the illumination values of neighboring pixels are similar to each other, so $i(x, y)$ can be regarded as one kind of low-frequency signal in an image. However, the reflectance will show the contrast arrangement of different composite materials (such as skin, eyebrows, eyes and lips, etc.) of this image. Therefore, $r(x, y)$ can be regarded as a high-frequency signal which closely corresponds to texture information of face.

Based on this understanding, our research uses the digital filtering approach to reduce the low frequency signal, and emphasize the high frequency signals of a face image at the same time. We expect to decrease the influence of background lighting on facial analysis and recognition. So the facial texture features can be strengthened to achieve the better face recognition accuracy.

The proposed illumination compensation method consists of (1) Homomorphic Filtering, (2) Ratio Image Generation, and (3) Anisotropic Smoothing, which are shown in Fig. 1.

1. Homomorphic Filtering

In reality, face images are influenced to many conditions and factors (such as lighting and face angle), so an original image may contain lot of noises. Therefore, we use a homomorphic filtering to adjust the image intensity by strength ening the high-frequency signal and decreasing the low-frequency signal.

First, we adopt the logarithm operation to separate the illumination and reflection coefficient from image, that is,

$$\begin{aligned} Z(x, y) &= \ln f(x, y) \\ &= \ln i(x, y) + \ln r(x, y) \end{aligned} \tag{2}$$

Next, we adopt the Fourier Transform to compute the left and right sides of the above equation,

$$F\{Z(x, y)\} = F\{\ln i(x, y)\} + F\{\ln r(x, y)\}$$
$$Z(u, v) = F_i(u, v) + F_r(u, v)$$

where $Z(u, v)$, $F_i(u, v)$ and $F_r(u, v)$ are the Fourier Transform results of $Z(x, y)$, $\ln i(x, y)$ and $\ln r(x, y)$ respectively. Then, we use a low-frequency filtering function $H(u, v)$ to multiply the above formula and get

$$\begin{aligned} S(u, v) &= H(u, v)Z(u, v) \\ &= H(u, v)F_i(u, v) + H(u, v)F_r(u, v) \end{aligned} \tag{3}$$

Furthermore, we use an inverse Fourier Transform to get

$$\begin{aligned} SS(x, y) &= F^{-1}\{S(u, v)\} \\ &= F^{-1}\{H(u, v)F_i(u, v)\} + F^{-1}\{H(u, v)F_r(u, v)\} \\ &= i'(x, y) + r'(x, y) \end{aligned} \tag{4}$$

where

$$i'(x, y) = F^{-1}\{H(u, v\}F_i(u, v)\}$$

$$r'(x, y) = F^{-1}\{H(u, v)F_r(u, v)\}$$

Finally, we apply the exponential operation to the above formula and obtain

$$\begin{aligned} g(x, y) &= e^{SS(x, y)} \\ &= e^{\{i'(x, y) + (r'(x, y)\}} \\ &= e^{i'(x, y)} e^{r'(x, y)} \\ &= i_0(x, y) r_0(x, y) \end{aligned} \tag{5}$$

After performing all of the above steps, $g(x, y)$ is the final filtered image. Because of $H(u, v)$ is a low-frequency filtering function, it will significantly reduce the intensity of low-frequency signal. So $g(x, y)$ can not only effectively preserve the high-frequency texture information, but also reduce the impact of illumination variation.

In general, $H(u, v)$ can be designed as

$$H(u, v) = (r_H - r_L)[1 - e^{-C[D^2(u, v)/D_0{}^2]}] + r_L \tag{6}$$

where $r_H > 1$, $r_L < 1$, and D_0 is a cut-off frequency. The constant c is a parameter to control the increasing degree of the exponential function. Fig. 2 shows an illustrating graph of $H(u, v)$.

The low-frequency signal not only includes the illumination information but also includes the texture information of human face image. So the r_L should be set to a small value but not zero, if we want not destroy the texture information of face image. Because of above reason, in order to remove the illumination information, we proposed the second steps: Ratio Image Generation.

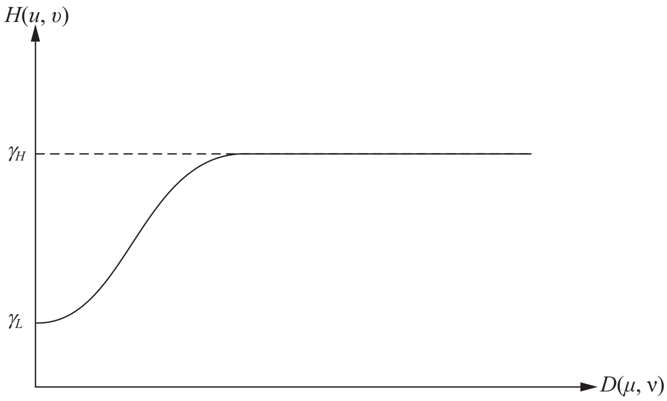

Fig. 2. A low-frequency filtering function *H*(*u*, *v*).

2. Ratio Image Generation

We have used the homomorphic filter to reduce the influence of illumination, but we cannot eliminate all low-frequency signals because the low-frequency signal may also contain some facial features which are useful to recognition. So instead of setting $r_L = 0$ to completely eliminate the low-frequency signal, r_L is set to be 0.5. Consequently, the filtered image still contains part of illumination information. For further reducing the illumination information, a second operation called "Ratio Image Generation" is proposed to eliminate the low-frequency signal. From the experiment, it clearly shows that using both of Homomorphic Filtering and Ratio Image Generation outperform than using Homomorphic Filtering only.

Since $g(x, y)$ denotes the value of a filtered image pixel, based on a Lambertian model [8], it can also be formulated as

$$g(x, y) = r(x, y) i(x, y) \tag{7}$$

where $r(x, y)$ is the albedo, and $i(x, y)s(x)$ is the illumination value of pixel (x, y). As described before, $r(x, y)$ denotes the texture information of the image and $i(x, y)$ denotes the low-frequency information. Let $W(x, y)$ be a smoothed image information by convoluting $g(x, y)$ with a Gaussian function G. That is

$$W(x, y) = g(x, y) * G. \tag{8}$$

Basically, the lighting factor can be implicitly attributed to W. Because both $i(x, y)$ and $W(x, y)$ correspond to the low frequency signal of an image at pixel (x, y), we can use $i(x, y) \approx c \times W(x, y)$ to present the approximate relationship between both low-frequency data and c is a constant value. If $g(x, y)$ is divided by $W(x, y)$, a new image $N(x, y)$ can be constructed which inherently reveals the high frequency attribute $r(x, y)$. That is

$$N(x, y) = \frac{g(x, y)}{w(x, y)} = \frac{r(x, y)\, i(x, y)}{w(x, y)} \approx cr(x, y) \tag{9}$$

where N can effectively reflect the intrinsic information of an image, which is called the ratio image.

3. Anisotropic Smoothing

While a ratio image N can effectively reflect the high-frequency signal of image, but it is very sensitive to noise. Therefore, we use an anisotropic smoothing operation to reduce the interference of noise. However, the general smoothing algorithms will not only reduce noise, but also undermine the image texture characteristics because they belong to high frequency signal. In order to reduce the noise effect and avoid the degeneration of normal texture information, we purposely design an anisotropic smoothing algorithm to produce the smoothed image. Here, some variables about the anisotropic smoothing operation are defined as below.

$N_{x,y}$ is the image value of pixel (x, y) in a ratio image

$$\begin{aligned} \Delta_E &= N_{x+1,y} - N_{x,y} \\ \Delta_W &= N_{x-1,y} - N_{x,y} \\ \Delta_S &= N_{x,y+1} - N_{x,y} \\ \Delta_N &= N_{x,y-1} - N_{x,y} \end{aligned} \tag{10}$$

Δ_E, Δ_W, Δ_S and Δ_N represent respectively the 4-directional image differences between pixel (x, y) and its adjacent image pixels. During the smoothing operation, a large degree of smoothing will be executed on the uniform parts of image, but a much small degree of smoothing will be executed on the boundary of image. Consequently, the smoothed image will preserve its boundary information effectively. To serve this purpose, a weighting function based on image difference is designed as

$$w_k = exp^{-\frac{\Delta_k \cdot \Delta_k}{\delta}} \quad \text{for } k \in \{E, W, S, N\} \tag{11}$$

where δ is the bandwidth parameter to control the change rate of the exponential function. Then, the smoothed image are computed by

$$g_{x,y}^t = g_{x,y}^{t-1} + \lambda(w_E g_{x+1,y} + w_W g_{x-1,y} + w_S g_{x,y+1} + w_N g_{x,y-1}) \tag{12}$$

where $g_{x,y}^t$ is the image value of pixel (x, y) after t times smoothing operations. Finally, in order to obtain more consistently filtered face images, a histogram equalization operation is applied to the anisotropic smoothed image.

III. EXPERIMENTS

In order to estimate the performance of the proposed method, the present study uses two famous face databases (Banca [13] and Yale database B [14]) to evaluate the recognition rate. The Banca database contains human frontal face images grabbed from several sections to reflect different variation factors. Among all sections, the section 1, 2, 3 and 4 of the "controlled" classification are used in our experiment. In each section, there are 10 images for each person, and in total there are 52 persons (26 males and 26 females), therefore it consists of 2,080 images in total. For performance comparison, we adopted three pattern matching methods (RAW, CMSM [7] and GDA [1]) to evaluate the recognition accuracy. RAW refers to the nearest-neighbor classification based on the image value in the Euclidean distance metric. CMSM (Constrained Mutual Subspace Method) constructs a class subspace for each person and makes the relation between class subspaces by projecting them onto a generalized difference subspace so that the canonical angles between subspaces are enlarged to approach to the orthogonal relation. GDA (Generalized Discriminant Analysis) adopts kernel function operator to make it easy to extend and generalize the classical Linear Discriminant Analysis to a non-linear one. Because CMSM needs to construct a mutual subspace, the images of 12 persons are selected to serve this end. Therefore, the face images of the rest 40 persons are used to test the recognition performance in this experiment. By randomly separating the 40 persons, different enrollment and unenrollment sets are constructed. An enrollment set contains the face images of the persons which have enrolled themselves to the recognition system and an unenrollment set contains the face images of the persons which have not enrolled to the system. During each random separation, there are 35 persons are selected in the enrollment set and 5 persons are in the unenrollment set. With this design, hundreds of experiments can be easily performed. Among the four sections, only the first section is used for serving the training purpose, and the other three sections are for testing. As for the Yale database B, it contains 5760 single light source images of 10 subjects each was taken pictures under 576 viewing conditions (9 poses × 64 illumination conditions). For every subject in a particular pose, an image with ambient (background) illumination was also captured. Hence, the total number of images is in fact 5760 + 90 = 5850. But we only test 1 pose (pose 0) of them; it means we only use 640 images to test the recognition rate. Then these 64 images are further separated into 6 sections (about 10 images per section), and only the first section is used for serving the training purpose, and the other five sections are for testing. Among 10 peoples, 5 of them are selected for enrollment, and the other 5 are for unenrollment.

The specific settings of parameters in our experiments are $r_H = 1.6$, $r_L = 0.5$, $D_0 = 15$, and $c = 10$. For CMSM, the base number is set 1000, and for GDA, the kernel sigma is set 4400 and its feature dimension is 200. Fig. 3 shows some images examples of which the first row is the original images, the second row is the images after applying the homomorphic filter, the third row is the ratio images, and the fourth row is the images operated by the anisotropic smoothing algorithm which indeed are the output images of our illumination compensation method.

Table 1. The recognition results of three different pattern matching methods on the compensated Banca face database.

	CMSM	RAW	GDA
FAR	4.6%	6.7%	6.1%
FRR	4.8%	7.3%	6.5%
RR	95.1%	92.6%	93.4%

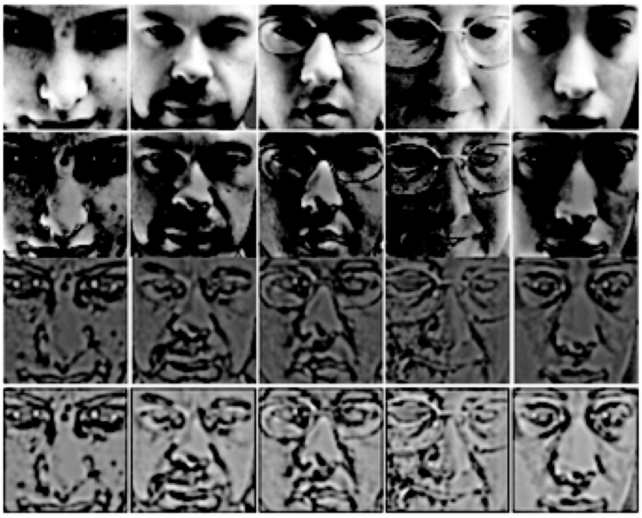

Fig. 3. Image examples of different processing steps, from the first row to the fifth row: input images, hormomorphic filtered images, ratio images, and anisotropic smoothed images.

Table 1 lists the recognition results of three different pattern matching methods, and FAR, FRR, and RR denote false accept rate, false rejection rate, and recognition rate individually. From this table, it shows all the recognition rates of the three recognition methods are larger than 90%, and the recognition rate of CMSM even is up to 95%. Thus, this experiment demonstrates that the compensated image by using the proposed approach can be further recognized by general recognition methods.

In addition, this study also compared the recognition rates with eight other illumination compensation methods: (1) Original, means we used original image to processing image without illumination compensation, (2) HE, means Histogram equalization method, (3) Retinex, (4) DCT means the Discrete Cosine Transform algorithm, (5) RA, means that we used ratio image generation + anisotropic smoothing, (6) HA is means homomorphic filtering + anisotropic smoothing, (7) LTV means Logarithmic Total Variation model, and (8) Gradient faces method. Besides, the recognition result of the original images is listed as a reference. Table 2 shows the experimental results to compare our algorithm with other compensated algorithms. Obviously, our method outperforms the other methods.

Because the Banca database does not contain images with significant illumination variation, we purposely used a few human face images from the Yale Face database [16] to demonstrate the effectiveness of our illumination compensation method. Visually, from Fig. 4, the original images in the first row show different appearances, but the final output images in the fourth row in fact appear quite similar to each other. Table 3 lists the recognition rates of our proposed method and the other illumination compensation algorithms with the Yale database B.

Table 2. Recognition results of different illumination compensation algorithms on Banca database.

Illumination Compensation Method	CMSM	RAW	GDA
Original	88.2%	57.6%	60.3%
Histogram equalization	88.5%	60.1%	64.3%
Retinex	81.5%	65.0%	75.4%
DCT	88.3%	85.1%	82.0%
RA	89.1%	88.3%	84.1%
HA	91.8%	85.0%	81.7%
LTV	92.3%	90.0%	90.6%
Gradient faces	92.5%	87.4%	90.7%
The proposed method	95.1%	92.6%	93.4%

Fig. 4. Image examples from Yale faces database. The first column to the third column is respectively "central-light source image", "left-light source image", and "right-light source image".

In Table 3, We can find the recognition rate of Yale database B can be up to 100%. It's because the Yale database B contains variation only in illumination and keeps other conditions (ex. background, pose, expression and accessory) the same.

Table 3. Recognition results of different illumination compensation algorithms and different databases.

Illumination Compensation Method	CMSM	RAW	GDA
Original	90.0%	82.6%	92.2%
Histogram equalization	96.1%	91.6%	97.9%
Retinex	95.8%	87.8%	97.8%
DCT	94.0%	88.0%	100.0%
RA	93.9%	83.7%	95.9%
HA	92.1%	87.6%	97.8%
LTV	86.2%	93.0%	98.2%
Gradient faces	94.1%	93.8%	100.0%
The proposed method	97.8%	95.6%	100.0%

However, the recognition rate of Banca database is lower (at most 95.1%) because it basically contains more variation and more peoples than Yale database B. So we can say the recognition of Banca database is more difficult than that of Yale database B. From the above experiments, it obviously shows that our purposed method consistently performs best than the other commonly used illumination compensation methods for the Banca, and Yale B face databases.

IV. CONCLUSION

In this paper, we propose a set of illumination compensation technique use for human face recognition. The proposed technique uses digital filtering to reduce the low-frequency signal and strengthen the high-frequency signal to reserve the facial texture information. And the proposed technique also can reduce the effect of background lighting change to increase the accuracy of face image recognition. Experiments have shown that the proposed method can achieve very promising recognition accuracy for the Banca database and Yale B faces database of each recognition method. It confirms the proposed algorithm is indeed more feasible and applicable. Actually, the proposed method is a general lighting compensation method which is not only limited in recognizing human faces. In the future, we will try to apply this method to other applications (such as OCR and Video surveillance).

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