An Improved Illumination Normalization based on Anisotropic Smoothing for Face Recognition

Sanghoon Kim, Sun-Tae Chung, Souhwan Jung, and Seongwon Cho

***Abstract*—**Robust face recognition under various illumination environments is very difficult and needs to be accomplished for successful commercialization. In this paper, we propose an improved illumination normalization method for face recognition. Illumination normalization algorithm based on anisotropic smoothing is well known to be effective among illumination normalization methods but deteriorates the intensity contrast of the original image, and incurs less sharp edges. The proposed method in this paper improves the previous anisotropic smoothing-based illumination normalization method so that it increases the intensity contrast and enhances the edges while diminishing the effect of illumination variations. Due to the result of these improvements, face images preprocessed by the proposed illumination normalization method becomes to have more distinctive feature vectors (Gabor feature vectors) for face recognition. Through experiments of face recognition based on Gabor feature vector similarity, the effectiveness of the proposed illumination normalization method is verified.

***Keywords*—**Illumination Normalization, Face Recognition, Anisotropic smoothing, Gabor feature vector.

I. INTRODUCTION

ROBUST face recognition under various illumination environments is not easy to achieve [1]. It is now well known that variation of illumination conditions can change face appearance dramatically so that the variations between the images of the same face due to illumination can be larger than image variations due to change in face identity [2] . There have been proposed several approaches to cope with the effects on face recognition due to illumination variations during the last decade. Early work for coping with illumination effects focused on image representations that are mostly insensitive to changes in illumination. Edge maps, 2D Gabor-like filters, first and second derivatives of the gray-level image, and the logarithmic transformations of the intensity image are among such image representations. However, none of the image representations was found to be sufficient by itself to deal with variations due to illumination changes [2]. Another approach is to seek an efficient method to compensate for illumination changes. [3] compares several illumination normalization algorithms for face recognition and shows that anisotropic smoothing-based normalization method [4] is more effective than other available illumination normalization methods. In general, real image $I(x,y)$ is regarded as product of reflectance $R(x,y)$ and illumination $L(x,y)$, that is $I(x,y)=R(x,y)L(x,y)$. Illumination is the amount of light falling on the object due to the light source. Reflectance is the amount of light reflected from the surface of the object and is an intrinsic property of an object, which is independent of illuminations. Illumination is usually supposed to change smoothly across the object so that illumination is more responsible for low frequency property of real image while reflectance is more responsible for high frequency property of real image. Since reflectance is independent of illumination, reflectance image is illumination normalized and can be successfully used for illumination invariant face recognition. However, computing the reflectance and the illumination from real images is, in general, an ill-posed problem. Thus, reflectance image estimated from anisotropic smoothing-based illumination normalization method cannot be completely independent of illumination effect even though it definitely shows reduced illumination effect. In fact, reflectance image contains small but different illumination component for each real image with different illumination change. Compared to the original real image, reflectance image estimated from anisotropic smoothing-based illumination normalization method shows less sharp edges and deteriorated intensity contrast while it achieves good illumination normalization.

Gabor feature-based face recognition like EBGM [5] which utilizes the Gabor feature vector similarity among face images is known to show good performance compared to other face recognition algorithms [6]. Gabor feature vector at a landmark of a face image reflects geometric properties around the landmark but also is affected by intensity information around the landmark. Thus, Gabor feature vector extracted from the reflectance image is not independent of illumination variations.

In this paper, we propose an improved anisotropic smoothing-based illumination normalization for face recognition utilizing Gabor feature vector similarity, which enhances edges of face images and reduces the deterioration of intensity contrast while it diminishes the effects of illumination variations.

Due to the enhanced edges and reduced deterioration of intensity contrast, the face images preprocessed by the proposed illumination normalization method produce more distinctive Gabor feature vector than those preprocessed by the previous anisotropic smoothing-based illumination normalization method. Thus, the Gabor feature-based face recognition shows better performance with respect to illumination variations when

Sanghoon Kim, Sun-Tae Chung and Souhwan Jung are with School of Electronic Engineering, Soongsil University, Seoul, Korea (e-mail: cst@ ssu.ac.kr).

Seongwon Cho is with A.I. Lab., Hongik University, Seoul, Korea.

gallery and probe face images are preprocessed by the proposed illumination normalization method rather than when gallery and probe face images are preprocessed by the previous anisotropic smoothing based-illumination normalization method. This fact is verified through experiments.

The rest of the paper is organized as follows. Section 2 explains Gabor wavelet, Gabor jet, Gabor jet similarity, and Gabor jet similarity-based face recognition which are the basic technical background necessary for understanding the works of the paper. Section 3 introduces the anisotropic smoothing-based illumination normalization method, and presents our proposed method. Experiment results are discussed in Section 4, and finally the conclusion is presented in Section 5.

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II. Face Recognition based on Gabor Jet Similarity

A. Gabor Wavelet, Gabor Jet, and Gabor Jet Similarity

The Gabor wavelet kernels used in this paper are represented as:

$$W(x, y, \theta, \lambda, \sigma) = e^{-\frac{1}{2\sigma^2}(\vec{x}\bullet\vec{x})} e^{i\vec{k}\bullet\vec{x}} . \qquad (1)$$

where $\vec{x} = (x, y)^t$, wave vector $\vec{k}$ is given as $\vec{k} = \left(\frac{2\pi \cos\theta}{\lambda}, \frac{2\pi \sin\theta}{\lambda}\right)^t$, θ represents wavelet direction, λ represents wave length , σ in (1) represents the size of Gaussian, and is proportional to λ . In this paper, we consider 40 Gabor wavelet kernels obtained by $\theta \in \{0, \frac{\pi}{8}, \frac{2\pi}{8}, \frac{3\pi}{8}, \frac{4\pi}{8}, \frac{5\pi}{8}, \frac{6\pi}{8}, \frac{7\pi}{8}\}$ and $\lambda \in \{4, 4\sqrt{2}, 8, 8\sqrt{2}, 16\}$ and $\sigma = \lambda$ in (1). The Gabor feature vector at an image point used in this paper means the complex Gabor wavelet coefficients obtained by convolving Gabor wavelet kernel with the intensity of the image point. Let us denote the Gabor feature vector obtained by convolving j-th one among the above 40 Gabor wavelet kernels with $I(x, y)$ (the image intensity at (x, y)) as $J_i(x, y)$. The Gabor feature vector $J_i(x, y)$ can be represented as $J_j(x, y) = \alpha_j(x, y) + i\beta_j(x, y)$ with real part $\alpha_j(x, y)$ and imaginary part $\beta_j(x, y)$. In this paper, we calculate each complex Gabor feature vector $J_j(x, y) = \alpha_j(x, y) + i\beta_j(x, y)$ by convolving j-th real and imaginary Gabor wavelet masks, which are precomputed from discretization of j-th Gabor wavelet kernel, with the image intensities at the point (x, y) respectively. Each Gabor wavelet mask is a two dimensional array that is used as a look up table for wavelet values during convolution.

Gabor jet means a collection of Gabor feature vectors from the same location in an image. In this paper, Gabor jet $J(x, y)$ at an image point (x, y) of an image is defined as the set $J(x, y) = \{J_j(x, y);\ j = 1, \ldots, 40\}$. Gabor jet at an image point (x, y) represents frequency information around the point, and is known as robust characteristics of objects [25].

Each Gabor feature vector $J_j(x, y)$ can be also represented as $J_j(x, y) = a_j(x, y) e^{i\phi_j(x, y)}$ with magnitude $a_j(x, y)$ and phase $\phi_j(x, y)$. Suppose $J_j^0 = a_j^0 e^{i\phi_j^0}$ is the j-th Gabor feature vector at (x_0, y_0) , and the Gabor jet at (x_0, y_0) is $J^0(x_0, y_0) = \{J_j^0;\ j = 1, \ldots, 40\}$. Then, Gabor jet similarity $S_\phi(J, J^0)$ between J and J^0 is defined [5] as:

$$S_\phi(J, J^0) \equiv \frac{\sum_{j=1}^{40} a_j a_j^0 \cos(\phi_j - \phi_j^0)}{\sqrt{\sum_{j=1}^{40} a_j^2 \sum_{j=1}^{40} (a_j^0)^2}} . \qquad (2)$$

B. Gabor Jet Similarity-Based Face Recognition

In this paper, we use 80 facial landmarks which consists of manually selected 25 landmarks (Fig. 1) and 55 landmarks obtained by interpolating manually selected 25 landmarks.

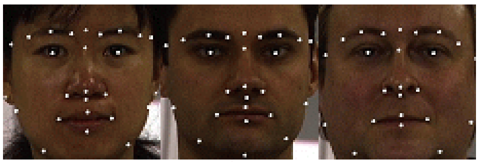


Fig. 1 Positions of 25 manually selected facial landmarks

Gabor jet-based face recognition algorithm adopted in this paper works as follows. In registration stage, the adopted face recognition algorithm first calculates Gabor jets of 80 landmarks for each gallery face image, and stores 80 Gabor jets for each gallery image for later comparison. In recognition stage, the adopted face recognition algorithm first calculates Gabor jets of 80 landmarks for the probe face image, and compares the 80 Gabor jets of the probe face image with the stored 80 Gabor jets of each gallery image one by one, and then determine the person of the test face image as the person of the face image in the gallery set which shows the highest Gabor jet similarity with the test face image.

All gallery face images and probe face images are rendered to have the same size and uprighted pose.

III. The Proposed Anisotropic Smoothing-Based Illumination Normalization

In this section, we present our proposed illumination normalization based on anisotropic smoothing illumination normalization, which is more effective for face recognition under various illumination environments. Before that, we need to introduce the anisotropic smoothing-based illumination normalization method proposed in [4].

A. Anisotropic Smoothing-Based Illumination Normalization

In general, an image $I(x, y)$ acquired by a camera is regarded as the product of two components, reflectance $R(x,y)$ and illumination $L(x,y)$, that is $I(x,y)= R(x,y)\ L(x,y)$ [7]. Illumination is the amount of light falling on the object due to the light source. Reflectance is the amount of light reflected from the surface of the object, is an intrinsic property of an object independent of illumination. Thus, if we use reflectance image, then we can reduce the effect of illumination variations.

Computing the reflectance and the illumination from real images is, in general, an ill-posed problem. However, on the assumption that illumination is close to the original image, but contains a smoothing constraint, Gross and Brajovic [4] found an approximate solution of illumination by minimizing the following cost function:

$$J(L) = \iint_{\Omega} \rho(x,y)(L-I)^2\,dxdy + \lambda \iint_{\Omega} (L_x^2 + L_y^2)\,dxdy \qquad (3)$$

where the first term forces illumination to be close to the original image and the second term imposes a smoothness constraint on illumination. And, Ω refers to the image, λ controls the relative importance of the two terms and $\rho(x,y)$ controls the anisotropic nature of smoothing constraint.

If we use the Euler-Lagrange equation for this calculus of variation problem, we can obtain the following differential equation.

$$L(x,y) + \frac{\lambda}{\rho(x,y)}(L_{xx}(x,y) + L_{yy}(x,y)) = I(x,y) \qquad (4)$$

$$\left(L_{xx}(x,y) \equiv \frac{\partial^2 L(x,y)}{\partial x \partial x}, L_{yy}(x,y) \equiv \frac{\partial^2 L(x,y)}{\partial y \partial y} \right)$$

Discretizing (4) on a rectangular lattice, we obtain the following discrete equation.

Then, reflectance $R(x,y)$ is obtained by $R(x,y) = I(x,y)\ /\ L(x,y)$. The histogram of the obtained reflectance $R(x,y)$ of the face image usually distributes narrowly around a pixel value. In order to make the reflectance images as much normal as

$$\begin{aligned} & L_{i,j} + \lambda\Big[\frac{1}{\rho_{i,j-1}}(L_{i,j} - L_{i,j-1}) + \frac{1}{\rho_{i,j+1}}(L_{i,j} - L_{i,j+1}) \\ & + \frac{1}{\rho_{i-1,j}}(L_{i,j} - L_{i-1,j})\Big) + \frac{1}{\rho_{i+1,j}}(L_{i,j} - L_{i+1,j}) = I_{i,j} \end{aligned} \qquad (5)$$

Where $L_{i,j}$ and $I_{i,j}$ means the value of $L(x,y)$ and $I(x,y)$ at (i,j) pixel location, and one usually modulates ρ by Weber's contrast, and thus $\rho_{i,j} = \frac{\Delta I}{I} = \frac{|I_i - I_j|}{\min(I_i, I_j)}$.

Equation (5) is a boundary problem and can be viewed as a large sparse matrix equation $AL = I$. Numerically equation (5) can be solved using multigrid methods [8]. After equation (5) is solved, the reflectance $R(x,y)$ is obtained by $R(x,y) = I(x,y) / L(x,y)$.

Fig. 2 shows original real images and reflectance images which are obtained from real images by the anisotropic smoothing based-illumination normalization. Reflectance images (d), (e) and (f) are corresponding to original real images (a), (b) and (c) respectively.

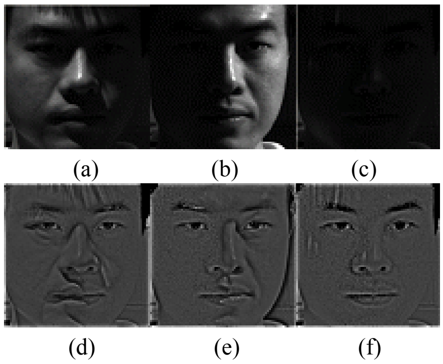
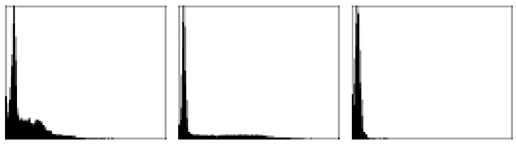
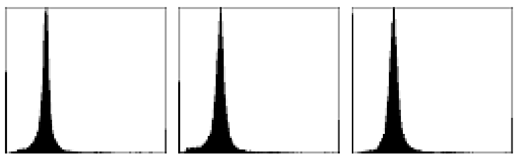


Fig. 2 Original real images (upper) and reflectance images (lower) obtained by anisotropic smoothing

As seen in Fig. 2, reflectance images are illumination normalized, that is, less illumination variant than the original images, and this fact can be verified by histograms shown in Fig. 3.



(a) Histograms of original images of Fig. 2 (a), (b) and (c)



(b) Histograms of reflectance images of Fig. 2 (d), (e) and (f)

Fig. 3 Histograms of original real images of Fig. 2 (upper) and histograms of reflectance images of Fig. 2 (lower)

While the histograms of real-images are quite different from each other, the histograms of reflectance images look similar since reflectance is an intrinsic property of the object. As seen in Fig. 3, the histograms of the reflectance images usually have narrow distribution around some pixel value. As explained before, the reflectance of real image is responsible for high frequency part of the real image. However, since anisotropic smoothing cannot separate reflectance from illumination completely (this is mainly due to the fact that computing the reflectance and the illumination from real images is, in general, an ill-posed problem), the reflectance image obtained by anisotropic smoothing contains some of illumination and loses some of high frequency components. Due to the results, feature vectors charactering geometric properties (ex. edges, geometric pattern, etc.), frequency properties, and texture properties (ex. intensity) around a landmark like Gabor feature vectors extracted from the reflectance image become less distinctive and are still affected by illumination conditions. Thus, face recognition using Gabor feature vectors under various illumination environments cannot be completely free from illumination conditions and will still have degraded performance compared to face recognition under a good illumination environment.

B. The Proposed Illumination Normalization Method

1) Outline of the Proposed Illumination Normalization Method

Strengthening low frequency components related with illumination and high frequency components which contributes to render edges shaper helps to make Gabor feature vectors more distinctive for face recognition. We propose an illumination normalization method effective for face recognition based on Gabor jet similarity, which enhances intensity contrast and edges while diminishing the effect of illumination variations. The proposed illumination normalization method proposed in this paper proceeds as follows.

As mentioned before, image is represented as product of reflectance $R(x, y)$ and illumination $L(x, y)$. First, the proposed method estimates illumination $L(x, y)$ through anisotropic smoothing. In order to enhance edges, after obtaining reflectance which is responsible for high frequency components by $R(x, y) = I(x, y) / L(x, y)$, the proposed method multiples the reflectance $R(x, y)$ by $\alpha\ (\alpha > 1)$. Next, in order to enhance intensity contrast, the proposed method applies histogram equalization to the illumination $L(x, y)$. Finally, the proposed method combines the scaled reflectance and histogram equalized illumination and scales the pixel values in the combined image so as to belong to the range of 8 bit pixel values, (0 ~ 255).

Thus, the final reconstructed image can be concisely represented as follows:

$$I(x, y)^{new} = scale(\alpha R(x, y) + Heq(L(x, y))) \qquad (6)$$

2) Edge Enhancement

As seen in Fig. 3 (b), the histogram of reflectance images has narrow distribution centering around some pixel value.

The proposed method multiplies the reflectance image $R(x, y)$ by $\alpha\ (\alpha > 1)$. This operation helps to enhance edges since reflectance is responsible for high frequency components of the real image and increasing pixel values of reflectance image contributes to fortify the high frequency components of the real image.

Fig. 4 shows reflectance images obtained by multiplying reflectance images of Fig. 2 by $\alpha\ (\alpha = 2)$. One can see that reflectance images in Fig. 4 looks sharper than reflectance images in Fig. 2.

Fig. 4 Enhanced reflectance images

3) Intensity Contrast Enhancement

Fig. 5 shows the illumination images obtained by anisotropic smoothing for the original real face images in Fig. 2.

Fig. 5 Illumination images of Fig. 2 (a), (b), and (c)

One can see that illumination images of Fig. 5 have low intensity contrast. Illumination is the major influential factor for determining the intensity contrast in real images. Thus, in order to enhance intensity in real images, we apply the histogram equalization to illumination images since histogram equalization are effective in increasing intensity contrast. Fig.6 shows the histogram equalized images for illumination images in Fig. 5.

Fig. 6 Histogram equalized images of Fig. 5 (a), (b), (c)

4) Final Image Reconstruction

The reconstructed image is obtained by combining the scaled reflectance and histogram equalized illumination and scaling the pixel values in the combined image so as to belong to between 0 and 255.

Fig. 7 Images preprocessed by the proposed illumination normalization about Fig. 2 (a), (b), (c)

One can see that images in Fig. 7 look sharper and have higher intensity contrast than those of Fig. 2 while effects of illumination are normalized.

Fig. 8 shows comparison between the previous illumination normalization method based on anisotropic smoothing and the proposed illumination normalization method.

Fig. 8 Top; Original real face images, Middle: face images illumination-normalized by the previous method, Bottom; face images illumination-normalized by the proposed method

IV. EXPERIMENTS

A. *Experiment Environments*

In order to verify the effectiveness of the proposed illumination normalization, we use two face databases, CMU PIE face database, and Yale face database B which are popularly adopted for testing the performance face recognition algorithms with respect to variations of illumination.

CMU PIE (Pose, Illumination, and Expression) face database [9] consists of 41,368 images of 68 people under 13 different poses, 43 different illumination conditions, and with 4 different expressions. Each image is JPEG with 640x486 pixels.

Yale Face database B [10] consists of 5,760 images of 10 people under 9 different poses and 64 different illumination conditions. Each image is grey image of pgm format with 640x486 pixels. The face recognition experiments in this paper first register face images in the gallery set, test face images in the probe set and determine the person of the test face image as the person of the face image in the gallery set which has the highest similarity with the test face image. The Gabor jet similarity is adopted for the similarity measure.

Each image in the gallery set and the probe set can be original as in the CMU PIE DB and Yale DB B or preprocessed by the anisotropic smoothing-based illumination normalization method or preprocessed by the proposed illumination normalization method. In order to focus more on analyzing the effectiveness of the illumination normalization methods with respect to illumination, we select the frontal images for gallery, and frontal or slightly rotated face images for probe sets (in CMU PIE DB, face images with face rotated to the right by 22.5°, and in Yale DB face images with face rotated to the right by 12°). The gallery images from CMU PIE DB are 58 images among 68 images with only ambient room light provided for gallery by CMU PIE DB. The excluded 10 images are images of 10 persons whose other face images in PIE DB have cutted chin. The gallery images from Yale DB B are frontal 10 images with ambient light. Fig. 9 and Fig. 10 show sample gallery images respectively from CMU DB and Yale DB.

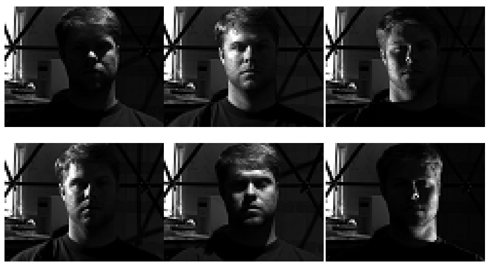
The ambient lighting conditions between CMU PIE DB and Yale DB B are very different since CMU PIE has room light but Yale DB B does not have room light.

Fig. 9 Sample of gallery images (CMU PIE DB)

Fig. 10 Sample of gallery images (Yale Face DB B)

The probe images from CMU DB and Yale DB are images under various illumination directions without ambient light. Fig. 11 and Fig. 12 show samples of probe sets.

Fig. 11 Sample of probe images (CMU PIE DB)



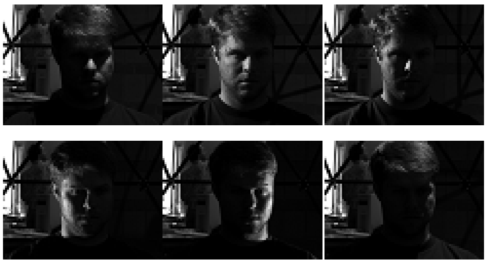


Fig. 12 Sample of probe images (Yale Face DB B)

B. Experiment Results

We did the following experiments with respect to 4 configurations of gallery and probe sets.

1) Test success rate of the face recognition algorithm based on Gabor jet similarity introduced in Section 2 using gallery images and probe images without illumination normalization.

2) Test success rate of the face recognition algorithm based on Gabor jet similarity introduced in Section 2 using gallery images and probe images preprocessed by the anisotropic smoothing-based illumination normalization.

3) Test success rate of the face recognition algorithm based on Gabor jet similarity introduced in Section 2 using gallery images and probe images preprocessed by the proposed illumination normalization.

The 4 configurations of gallery and probe sets are explained in Table I.

TABLE I
CONFIGURATION OF GALLERY SET AND PROBE SET CONFIGURATION

<table>
<tr><th>Configurations</th><th>Gallery set</th><th>Probe set</th></tr>
<tr><td>1</td><td rowspan="4">58 images form CMU PIE and 10 images form Yale DB B</td><td>1218 frontal images from CMU PIE</td></tr>
<tr><td>2</td><td>1218 images with 22.5°right rotation from CMU PIE</td></tr>
<tr><td>3</td><td>640 frontal images from Yale</td></tr>
<tr><td>4</td><td>640 images with 12°right rotation from Yale</td></tr>
</table>

The experimental results are summarized in Table II. The data in Table II shows the effectiveness of illumination normalization and the proposed method is more effective than the previous anisotropic smoothing-based method for face recognition.

TABLE II
COMPARISONS OF ILLUMINATION NORMALIZATION METHODS FOR FACE RECOGNITION

Illumination Normalization method	Conf. 1	Conf. 2	Conf. 3	Conf. 4
No Normalization	64.9	78.38	96.38	66.46
Anisotropic Smoothing	96.4	82.86	99.38	76.62
Proposed One	97.2	84.48	100	86.77

The effect of illumination variations can be more dominating than the effects of other facts like local geometric property around landmarks in case that gallery images and probe images have the similar frontal poses. Thus, in case of no illumination normalization, the performance of the face recognition for configuration 1 is worse than that for configuration 2 even though they use the same gallery set but configuration 1 uses the probe set with easier pose than configuration 2. The gallery images and probe images of configuration 3 have the almost same pose which explains why success rate of the face recognition in configuration 3 is much higher than those of other configurations.

The remarkable performance gaining of the proposed illumination normalization method over other methods in configuration 4 is explained as follows. The difference of ambient lighting conditions between the gallery images and the probe images in configuration 4 are effectively reduced by the proposed method which achieves intensity contrast enhancement while diminishing the effects of illumination variations. Thus, when the proposed one is applied for gallery and probe images in configuration 4, Gabor jet similarity is rendered to be determined more by the intrinsic nature of facial features.

V. CONCLUSION

In this paper, we proposed an effective illumination normalization method for face recognition using Gabor jet similarity under various illumination environments. The propose method enhances edges and intensity contrast while diminishing the effects of illumination variations. Due to these improvements, the Gabor feature vectors extracted from images preprocessed by the proposed illumination normalization method is more distinctive than Gabor feature vectors extracted from images preprocessed by the previous anisotropic smoothing-based illumination normalization method or any other methods. The effective ness of the proposed method is verified using face recognition algorithm based on Gabor jet similarity.

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