Integral Normalized Gradient Image — A Novel Illumination Insensitive Representation

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Abstract

In this paper, we present a novel illumination insensitive image, called integral normalized gradient image (INIGI), for face recognition. Unlike previous model-based methods, which require training images or have many str constrains for implementation, the proposed representation is simple and generic. Based on the intrinsic and extrinsic factor definition, we firstly normalized the gradient with a smoothed version of input image and then integrate the result into new grayscale image. To avoid unwanted smoothing effects on step edge region, anisotropic diffusion method is introduced. Experiment results on FRGC DB prove that our new approach is very effective in improving verification rate for both holistic and local features.

1. Introduction

Illumination is the one of the main difficulties, which affects the performance of face recognition system. The reason beneath this phenomenon is due to the fact that in spite of different feature extraction feature methods, e.g. PCA [1], LDA [2], Gabor [3], most of the popular methods are appearance-based method and little illumination direction variation can significantly change the appearance of face image.

According to recent report on FRGC v2.0 [14], the best verification rate at FAR=0.001 is about 98% under controlled scenarios (Experiment 1) where the illumination condition is strictly limited to near frontal direction variation. While in the uncontrolled environment (Experiment 4) the verification rate at FAR=0.001 is only about 76%. The main difference between these two experiments is the illumination, shown in Figure 1.

(a) Images in Exp 1 (b) Images in Exp 4
Figure 1. Illumination difference between Experiment 1 and Experiment 4

Recently many algorithms [5-9] have been proposed to deal with this problem and these can be categorized into two main approaches, model-based and signal-based. Model-base approach, such as illumination cone [8], spherical harmonic [9] and quotient image [5] takes the advantage of 3D or 2D model from training data to compensate the illumination variation. However the 3D or 2D model is not accessible in many practical applications. The Reintex method [7] by R. Gross and V. Brajovic and SQI method [6] by H. Wang etc. belong to the signal-based approach, which is simple and generic and does not need any training images. Our new algorithm falls into the second category.

The arrangement of this paper is as follows. In first section, we analyze the illumination property of face images and define the intrinsic and extrinsic factor for face recognition. Based on analysis, the new algorithm, INGI, is introduced in section 2. The implement detail of the new algorithm is provided in section 3. Finally we present the experiment result and make a conclusion about this method.

2. Illumination Analysis

Generally speaking, the image of 3D object can be roughly described by Lambertian model.

$$I = \rho n^T \bullet s \qquad (1)$$

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The equation (1) represents that the grayscale of 3D object image comes from 3 factors, texture *?*, 3D shape $\boldsymbol{n}$ and illumination $\boldsymbol{s}$. This relationship is shown in figure 2.

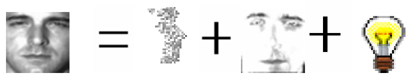


Image = 3D Shape + Texture + Illumination

Figure 2 Image from illumination, shape and texture

Except for nose region, most part of human face is relatively flat and continuous. Moreover all faces from different person have very similar 3D shape $\boldsymbol{n}^T$. This characteristic can be partial proved by our empirical experience that warping the texture of different person's texture into a generic face shape does not seriously affect the identity of each person. Quotient image method has taken advantage of this virtue for extracting illumination invariant feature. Therefore the texture information takes an important role in face recognition.

According to the equation (1), we can also conclude that $n^T \bullet s$ is an illumination sensitive part in the imaging model. Even if there is a very little lighting direction variation in FRGC 2.0 target images, an obvious image variation, shown in Figure 3, can appear.

(a) Right Lighting (b) Left Lighting

Figure 3 Samples images in target set after histogram equalization

We define the ρ as the **intrinsic factor** and $n^T \bullet s$ **extrinsic factor** for face recognition. The intrinsic factor is illumination free and represents the identity, whereas extrinsic factor is very sensitive to illumination variation and only partial identity information is included in the 3D shape $\boldsymbol{n}^T$. In addition, the illumination problem is the well known ill-posed problem. Without any additional assumptions and constrains, no analytical solution can be deduced only from the input 2D image. Previous approaches, such as illumination cone and spherical harmonic methods, directly take the 3D shape $\boldsymbol{n}^T$ as known parameter or can be estimated by training data. However in many practical systems, these requirements are inaccessible. Though quotient image algorithm does not need the 3D information, its application scenario is limited to point lighting source [6].

Our definition of intrinsic and extrinsic factor is also based on Lambertian model with point lighting source, however this definition can be extended to any type of lighting sources by combination of point lighting sources, show in Equation (2).

$$I = \rho \sum_i n^T \bullet s_i \tag{2}$$

In short, enhancing the intrinsic factor and depressing the extrinsic factor in the input image can achieve illumination insensitive image. Our INGI approach is based on this idea.

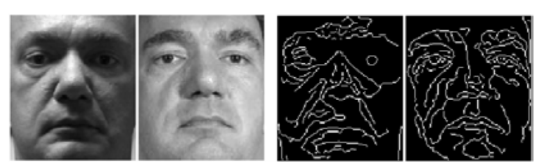
3. Integral Normalized Gradient Image (INGI)

According to analysis in previous section, the intrinsic factor mainly contains the skin texture, which has sharp spatial variation and the extrinsic factor, the shading part, includes the illumination and 3D shape. Except for nostrils and open mouth, the shading is continuous and relatively has slow spatial variation.

Therefore we can make the following assumptions:

1. The intrinsic factor locates almost in high spatial frequency domain.
2. The extrinsic factor locates almost in low spatial frequency domain.

The direct application of these assumptions is high-pass filter. However it has been proved [11] that this kind of filter is not robust to illumination variation, shown in Figure 4. Moreover this kind of operations almost removes the useful intrinsic factor.



(a) Original Images (b) edge map

Figure 4 Illumination sensitive edge

In fact, this result can be deduced by the equation (1) and our two assumptions.

The gradient operation can be written as

$$\nabla I = \nabla(\rho n^T \bullet s) \approx (\nabla \rho) n^T \bullet s = (\nabla \rho) W \tag{3}$$

where $\boldsymbol{W}$ is the scaling factor by the shading $n^T \bullet s$.

Retinex method [7][10] and SQI method [6] assume similar smoothness characteristic for illumination as those of ours. They use the smoothed images as the estimation of this extrinsic part. We make the same procedure to estimate the extrinsic factor.

$$\hat{W} = I * G \tag{4}$$

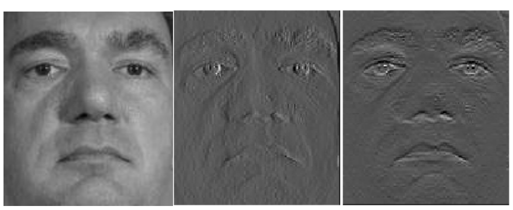
where $\boldsymbol{G}$ is the smoothing kernel.

To overcome the illumination sensitivity, we normalized the gradient map by the following equation.

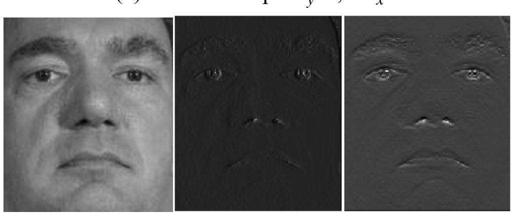
$$N = \frac{\nabla I}{\hat{W}} \approx \frac{(\nabla \rho)W}{\hat{W}} \approx \nabla \rho \tag{5}$$

Because $\hat{W}$ is the smoothed image, which can be taken as the estimation of extrinsic factor, the illumination effect is removed from the gradient map after this normalization.

After the normalization, the texture information in normalized image $\boldsymbol{N}$ is still unobvious and the image is very noisy due to the high-pass gradient operation. To recover the texture and remove the noise, we integrate the normalized gradient and acquire the integral normalized gradient image, shown in Figure 5.



(1) Gradient map $\nabla_y I$, $\nabla_x I$



(2) Normalized Gradient Map $\boldsymbol{N_x}$, $\boldsymbol{N_y}$

(3) Integral Normalized Image

Figure 5 Gradient map and normalized gradient map

There are two reasons for integration operation. Firstly we can recover the texture by integrating the gradient image. Secondly after the division operation in equation (5), the noise information is intensified and the integration operation can smooth the image.

4. Implementation

The framework of INGI is displayed in Figure 6.

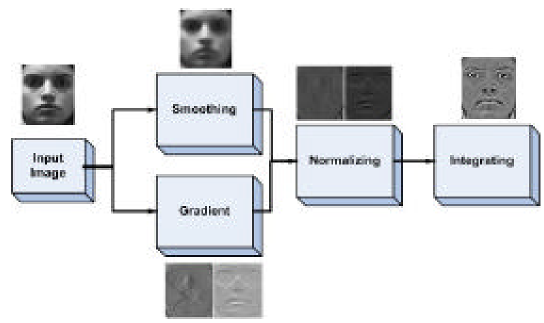


Figure 6 Overview of INGI

To summarize the procedure above, we have the following three steps,

(1) Acquire gradient map by Sobel operator
(2) Smooth the image and calculate normalized gradient image
(3) Integrate the normalized gradient map

For the third step, the task is to recover the grayscale image from its gradient map.

In fact, if given initial grayscale value of one point in the images, we can estimate the grayscale of any point by simply integration. However the result may be different due to different integral road.

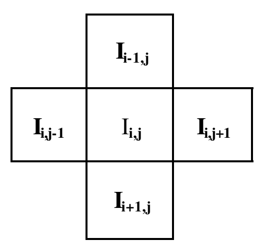


Figure 7 Four neighborhoods used in Equation (6)

An alternative method is by iterative diffusion method, shown in the following.

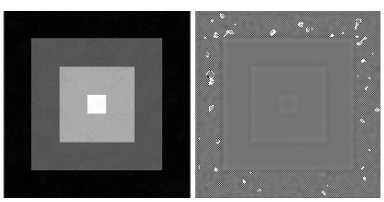
$$I_{i,j}^{t}=\frac{1}{4}\left[\begin{array}{l}\left(I_{i,j}^{t-1}+\nabla_{N}I\right)+\left(I_{i,j}^{t-1}+\nabla_{S}I\right)\\+\left(I_{i,j}^{t-1}+\nabla_{W}I\right)+\left(I_{i,j}^{t-1}+\nabla_{E}I\right)\end{array}\right] \quad (6)$$

where
$$\nabla_N I = I_{i-1,j} - I_{i,j}$$
$$\nabla_S I = I_{i+1,j} - I_{i,j}$$
$$\nabla_W I = I_{i,j-1} - I_{i,j}$$
$$\nabla_E I = I_{i,j+1} - I_{i,j}$$
and usually $I^0 = 0$.

However this isotropic method has one shortcoming, it blurs the image in step edge region, shown in Figure 8. To overcome this weakness, we adopt an anisotropic approach [12].

Let the gradient of image be $\nabla_y I_{i,j} = I_{i,j} - I_{i-1,j}$ and $\nabla_x I_{i,j} = I_{i,j} - I_{i,j-1}$, then

$$\begin{aligned}\nabla_N I &= I_{i-1,j} - I_{i,j} = -\nabla_y I_{i,j}\\ \nabla_S I &= I_{i+1,j} - I_{i,j} = \nabla_y I_{i+1,j}\\ \nabla_W I &= I_{i,j-1} - I_{i,j} = \nabla_x I_{i,j}\\ \nabla_E I &= I_{i,j+1} - I_{i,j} = \nabla_x I_{i+1,j}\end{aligned} \quad (7)$$

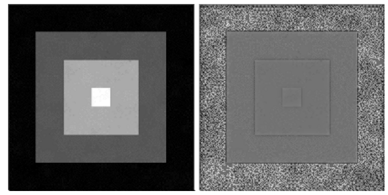


(1) Original image (2) Recovered image
Figure 8 Image recovered by isotropic method

$$I_{i,j}^{t} = I_{i,j}^{t-1} + \lambda\left[\begin{array}{l}C_N\left(I_{i,j}^{t-1}+\nabla_N I\right)+C_S\left(I_{i,j}^{t-1}+\nabla_S I\right)\\+C_W\left(I_{i,j}^{t-1}+\nabla_W I\right)+C_E\left(I_{i,j}^{t-1}+\nabla_E I\right)\end{array}\right] \quad (8)$$

$C_K = \dfrac{1}{1+\left\|I_{i,j}^{t-1}+\nabla_K I\right\|/G}$, where K ? {N, S, W, E}, $I^0 = 0$, and G is a scaling factor; ? controls the update speed.

If ? is too large, we may not get stable result and it is set to 0.25 in our experiment.



(1) Original image (2) recovered image
Figure 9 Image recovered by anisotropic method

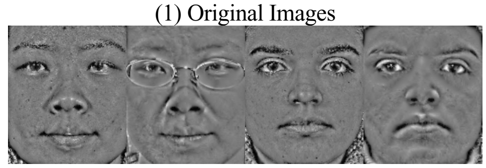
Compared with the result in Figure 8, the recovered image in Figure 9 is edge-preserved and numerical stable.

4. Experiment Results and Discussion

We test our novel approach on FRGC DB v1.0a and v2.0. In v1.0a, there are 275 subjects and 7544 recordings and there are 466 subjects and 32,056 recordings in V2.0. There are 3 experiments, experiment 1, 2 and 4, for 2D image recognition and we focus on experiment 4, which has large illumination changes (indoor uncontrolled). FRGC Technical Report [14] has more details about the database and experiment.

The illumination normalization effects and some of samples in experiment 4 are shown in Figure 10. INGI can depress the illumination of original image and enhance the face texture especially for highlight and shadow region. It's clear that the illumination sensitive, shading part is almost removed in these images.

(1) Original Images



(2) INGI
Figure 10 Illumination normalization effects

Our verification experiment takes the original images without our preprocessing but with simple histogram equalization as the baseline method and the Nearest Neighbor (NN) as classifier. Two kinds of features, global (PCA) and local (Gabor) feature are used to verify the generalization of INGI. The verification rate and EER on V1.0 are displayed in Figure 11 and Figure

12. We also compare our result with that of SQI to further testify the performance.

It is clear that the verification rate at FAR=0.001 (FRR_0.001) are obviously improved for both global and local feature.

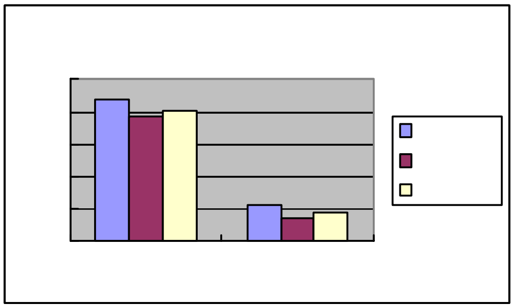


Figure 11 Verification result on Gabor feature (original, SQI, INGI)

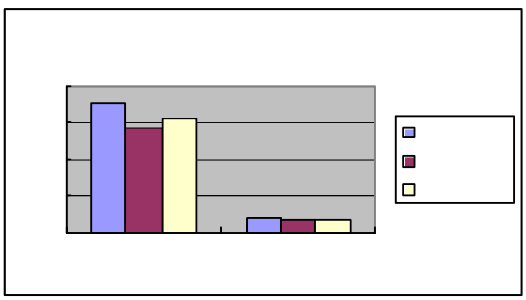
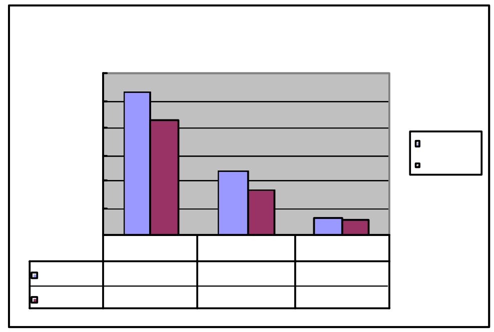


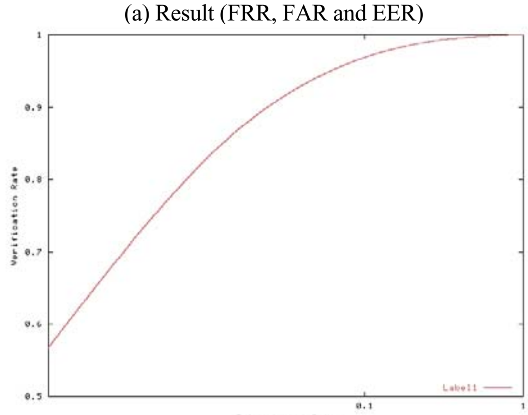
Figure 12 Verification result on PCA feature (original, SQI, INGI)

In addition, our new algorithm also achieves a little improvement compared with SQI methods, though we have very similar transformation as that of SQI. To avoid the noisy effect in the division operation in equation (5), the new method takes the advantage of integral and anisotropic diffusion to make more smoothing and steady result. Because our aim is to testify the effectiveness of preprocessing, only a simple NN classifier is used and the performance is not good enough compared with the baseline result by BEE system.

To further check the validness of our new algorithm, we also carry out experiment on much larger database V2.0 by Advanced Face Descriptor [4][13] feature extraction and recognition method, which is a mixture of global and local feature. Because the FRGC DB is collected within several years, there are 3 masks, maskI, maskII and maskIII in v2.0 Exp4, which control the calculation of the verification (FRR, FAR and EER) within the same semester, within the same year and between semesters respectively. The verification result calculated by BEE [14] shown in Figure 13-15 demonstrates that our new method increases at least 10 percent in performance for all three masks.

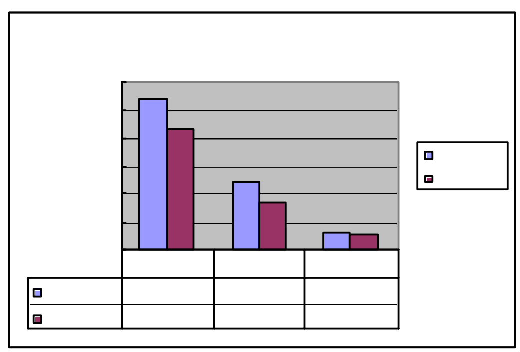


(a) Result (FRR, FAR and EER)

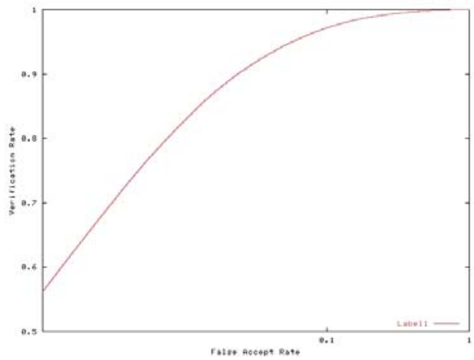


(b) ROC Curve by BEE

Figure 13 Verification Result with mask I

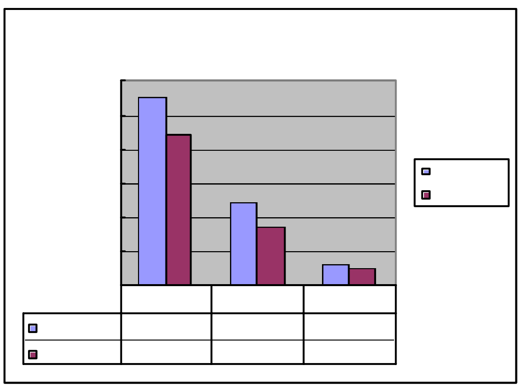


(a) Result (FRR, FAR and EER)

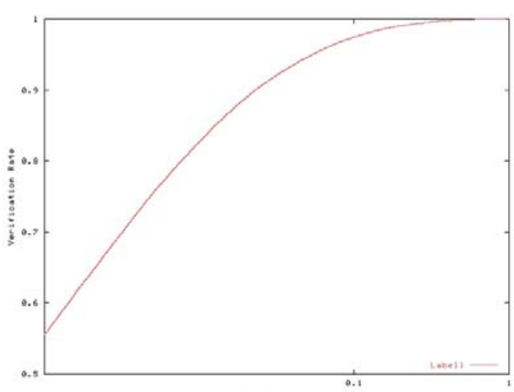


(b) ROC Curve by BEE

Figure 14 Verification Result with mask II



(a) Result (FRR, FAR and EER)



(b) ROC Curve by BEE

Figure 15 Verification Result with mask III

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5. Conclusion

We advance a new algorithm for illumination normalization. Based on the analysis of the face-imaging model and definition of intrinsic and extrinsic factors, we make a reasonable assumption and propose the integral normalized gradient image as an illumination insensitive representation. To avoid the blurring effect in edge region, we adapt anisotropic diffusion method in the implementation of INGI. The experiment on FRGC data demonstrates the effectiveness of our new algorithm.

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