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AN ADAPTIVE ILLUMINATION PREPROCESSING METHOD FOR FACE RECOGNITION

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Abstract

Illumination variation is one of the most important challenges in face recognition, because changes to illumination conditions have a significant effect on performance. However, most illumination preprocessing methods apply the same level of processing to all facial images, without considering their unique illumination conditions. Therefore, the performances of existing preprocessing methods are limited when dealing with varying illumination conditions. In this paper, we propose an adaptive illumination preprocessing method for face recognition, which adaptively preprocesses each face image according to its illumination condition. The proposed method first uses the illumination quality index (IQI) to describe the illumination. Then, we create an adaptive parameter adjustment model for the illumination preprocessing method. Finally, the proposed model adjusts the parameters of the illumination preprocessing method based on the IQI of the facial image, and enhances the preprocessing effect. Our extensive simulation results show that the proposed method can effectively improve the performance of face recognition under varying illumination conditions, when compared with existing methods.

Key Words

Face recognition, illumination normalization, illumination quality index, adaptive

1. Introduction

Face recognition has attracted a great deal of attention because it has important theoretical significance and extensive applications. After more than 40 years of development, research on face recognition has made great achievements, but still faces a lot of challenges, such as light, posture, facial expression, and so on. Variations between the same face under different illumination conditions are almost larger than variations between different faces under the same illumination conditions [1], so accounting for illumination variations has become one of the most important challenges in face recognition [2]. The developers of the famous commercial face recognition system Face Recognition Vendor Test [3] also noted that the illumination problem is one of the main factors affecting the performance of face recognition systems. Thus, image processing is important [4]. To deal with the illumination problem, a number of methods have been proposed over the past decades. They can be divided into three categories: illumination variation modeling, extracting illumination insensitive features, and illumination normalization [5]. Shi *et al.* [6] proposed a novel illumination balance algorithm based on the improved affine shadow formation model proposed, which belongs to the second category. Among these approaches, illumination normalization approaches are the most simple and effective. The purpose of illumination normalization is to compensate for or eliminate changes in illumination, and obtain an illumination normalized facial image. Illumination normalization methods can be divided into two categories. The first is based on traditional image processing methods. The widely extensively used logarithmic transformation (LT) method [1], gamma intensity correction (GIC) method [7], histogram equalization (HE) method [8], histogram specification (HS) method [8], local regularization method [9], and recently proposed adaptive block HE method [10] are in this category. The second category is based on retinex theory methods. The basic idea of these methods [11], [12] is to decompose the facial image into a smooth illumination component and an illumination-invariant reflection component. The reflection component is used for face recognition. The multi-scale retinex (MSR) method [13], anisotropic smoothing method [14], self-quotient image (SQI) method [15], log-domain discrete cosine transform (LogDCT) method [16], [17], logarithm total variation (LTV) model [18], and small-and-large-scale (S&L) method [19] belong to this category.

Although the above methods can handle the illumination problem and improve facial recognition results, they preprocess all the facial images in the same way, regardless of their individual illumination conditions. Therefore, there is a need to further improve these methods by considering the illumination conditions of each image.

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Recent studies also pointed out this problem [20]–[24]. Arandjelović and Cipolla [20] and Han *et al.* [21] noted that facial images under varying illumination conditions require the same preprocessing operations, which simultaneously have positive and negative effects. By positive effect, we mean that a face that is incorrectly recognized before preprocessing is correctly recognized after preprocessing. Facial images can be decomposed into illumination and reflection components, and illumination normalization can weaken both components at the same time. In practice, facial images taken in normal illumination conditions are typically used as gallery images. Therefore, if we consider a probe image under extreme illumination, the illumination difference between the probe and gallery images will be much larger than any intrinsic difference. Illumination normalization can significantly weaken the illumination differences without removing too many facial features, which can lead to positive results. If the probe image was taken under normal illumination conditions, the effect is the opposite. In this paper, we show that when there are dramatic changes, illumination preprocessing can have a positive effect, and if illumination conditions are relatively normal, the same degree of illumination preprocessing will have a negative effect. Therefore, illumination normalization should depend on the illumination condition of the facial image. Sellahewa and Jassim [22] used the image luminance index [23] to measure facial image quality, where the image luminance index represents the average intensity. The image luminance index was used to adaptively select fusion parameters for wavelet-based multistream face recognition, which improved the recognition rate to a certain extent. The image luminance index only represents the average intensity, and cannot sufficiently evaluate image quality, so the improvement using this method is small. Ren *et al.* [24] proposed a better qualitative analysis index for facial image illumination called the illumination quality index (IQI). IQI represents the probe image's degree of normal illumination conditions. They avoided the negative effects of illumination normalization to some extent, and improved the recognition rate by avoiding preprocessing images with high IQI values. However, Ren *et al.* [24] only avoided preprocessing a few images with high IQI values, the other images were preprocessed in the same way. So, the method in [24] is only part of the adaptive illumination preprocessing step, and cannot determine the required extent of illumination preprocessing based on the illumination conditions. To solve this problem, we propose a complete adaptive illumination preprocessing method. First, we estimated the facial image illumination under varying illumination conditions and completed a qualitative analysis. Then, we built an adaptive parameter adjustment model that can determine the parameter of the illumination preprocessing method according to our qualitative analysis of the illumination in the facial image. Finally, we developed a method that adaptively preprocesses the illumination of the image.

The remaining sections of this paper are organized as follows. In Section 2, we describe the method for evaluating the illumination quality and our illumination quality qualitative analysis. The adaptive illumination preprocessing method is described in detail in Section 3. Our experiments and analysis on the Extended YaleB face database are presented in Section 4. Finally, Section 5 contains a summary of the work in this paper.

2. Evaluation of Illumination Quality

The proposed method preprocesses facial images according to their illumination conditions, so we must first evaluate the illumination quality of the images. The discrete cosine transform [16] has an energy gathering effect, so it can concentrate the energy in the low-frequency part of the image. Additionally, the illumination component of a facial image is mainly located in its low-frequency part, so the discrete cosine transform can be used to estimate the illumination by retaining the low-frequency part of the image. Thus, in this paper, we used the discrete cosine transform to estimate the illumination.

We use theIQI of a facial image in this paper. It is defined as the similarity between the illumination estimate of a probe image and a reference image. The similarity is calculated using the cosine similarity angular distance. IQI is defined as follows:

$$\mathrm{IQI}(I_p) = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} L_p(i,j) \times L_r(i,j)}{\| L_p\| \times \| L_r\|} \tag{1}$$

where $\mathrm{IQI}(I_p)$ represents the IQI of the probe image I_p; $L_p(i,j)$ and $L_r(i,j)$, respectively, represent the pixel values of the probe image illumination estimate and the reference image illumination estimate at each point (i,j); and the symbol $\| \ \|$ represents the L_2 norm.

The reference image is a front facial image taken under normal illumination conditions. Because IQI is the similarity between the illumination estimates of the probe and reference images, it can represent the illumination in the probe image, and can be used to evaluate its illumination quality. Based on their analysis of the Extended YaleB facial database's IQI values, Ren *et al.* [24] concluded that IQI is an effective measure of illumination changes.

The computational complexity of the proposed method can be split into four parts: ranking the whole training set according to IQI, determining the appropriate parameter for each illumination level, establishing the adaptive parameter adjustment model, and calculating the reflection component of the facial image. We define n as the number of training images, and h and w as the height and width of each image. The computational complexity of ranking the training set according to IQI is $O(nhw)$. The computational complexity of determining the parameter of each illumination level is $O(100nhw)$. The computational complexity of establishing the adaptive parameter adjustment model is $O(n^2)$. The computational complexity of calculating the reflection component is $O(hw)$. So, the overall time complexity of this method is $O(nhw + n^2)$.

3. Adaptive Illumination Preprocessing Based on the LTV Model

Traditional illumination preprocessing methods such as MSR, SQI, and LTV preprocess all the illumination images in the same way. On the basis of an evaluation of the quality of an image's illumination, we propose an adaptive illumination preprocessing method. First, the method calculates the IQI according to the illumination conditions of the facial image. Then, based on the IQI, we build the illumination preprocessing method's adaptive parameter adjustment model, which can adjust the parameters of the traditional illumination preprocessing methods according to the illumination conditions. It was demonstrated experimentally in [17] that the LTV model is a particularly good facial illumination preprocessing method and performs better than other common methods such as MSR and SQI. Additionally, the LTV model only has one parameter that must be determined. Therefore, we have chosen it for our implementation of an adaptive illumination preprocessing method. In this section, we first introduce the LTV model, and then method for selecting its parameter. Finally, we describe the adaptive parameter adjustment model and how it is trained.

3.1 LTV Model

The LTV model is an excellent illumination preprocessing method based on retinex theory, which we explain in Section 3.1.1. The illumination estimate is the most important part of the LTV model because it directly determines the effectiveness of the illumination preprocessing method. Section 3.1.2 describes the LTV's illumination estimation method, that is, the analysis of total variation (TV) model. Finally, we introduce the illumination preprocessing method based on the LTV model in Section 3.1.3.

3.1.1 Retinex Theory

The retinex model is extensively used in facial recognition to remove the influence of illumination. According to retinex theory, a facial image can be formed by the product of the reflectance and illumination components, that is,

$$I(x,y) = R(x,y) \times L(x,y) \tag{2}$$

where $I(x,y)$ is the intensity of an image, $R(x,y)$ is the reflectance, and $L(x,y)$ is the luminance at location $(x,y) \cdot$ $R(x,y)$ is the intrinsic property of the face and can be used as an illumination-invariant property for facial recognition. Taking the logarithm of (2) we obtain

$$\log I(x,y) = \log R(x,y) + \log L(x,y) \tag{3}$$

Let $i = \log I(x,y)$, $r = \log R(x,y)$, and $l = \log I(x,y)$. Then,

$$r = i - l \tag{4}$$

The logarithmic transform does not change the monotonicity of a function, so r has the same properties as $R(x,y)$ and can be used as an illumination-invariant property for facial recognition. According to (2)–(4), the reflectance (r) can be calculated using the log-domain facial image minus the log-domain illumination. So, the key to the retinex theory method is to estimate the illumination component in the logarithmic domain.

3.1.2 Illumination Estimation Based on TV

TV is a classic image restoration method. It accurately retains edges when applied to image smoothing, preserving the edges and details while smoothing the image. Taking advantage of this property, it can be used as an excellent illumination estimation method. Using TV as a low-pass filter for illumination estimation, we obtain

$$\hat{l} = \arg\min \int_{\Omega} (|\nabla l| + \lambda \|i - l\|_{L1} dxdy \tag{5}$$

where $\hat{l}$ is the optimal solution of restored image l. It represents the illumination component of image i. $\int(\nabla l)$ is the total variation of l, which controls the smoothness of l. ∇l and $|\nabla l|$ are the gradient and gradient magnitude of l, respectively; and $\int \|i - l\|_{L1}$ specifies the similarity between l and i. The minimization of $\int \|i - l\|_{L1}$ preserves the edges of l. λ is a regularization parameter that plays an important role in balancing these two terms. A smaller λ will increase the smoothness. The whole equation guarantees that the model can smooth an image and maintain the edges of objects at the same time.

3.1.3 Illumination Preprocessing Based on TV

The illumination preprocessing method based on LTV is shown in Fig. 1.

3.2 Parameter Selection of the LTV Model

Equation (5) implies that the parameter selection of the LTV adaptive illumination preprocessing method is very important. According to our experience, for 100×100-sized images, a reasonable parameter value is in the range between 0 and 1. Figure 2 shows the results of the LTV

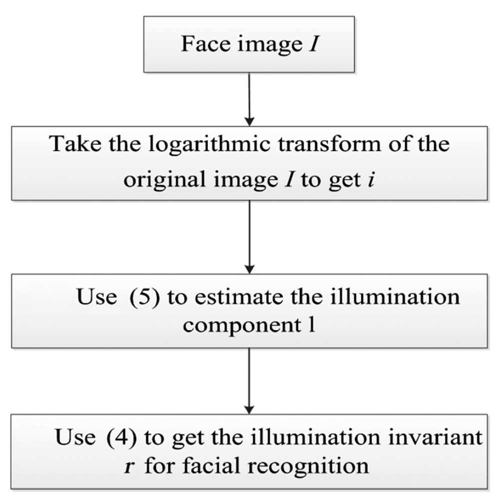

Figure 1. Flowchart of the illumination preprocessing method based on LTV.

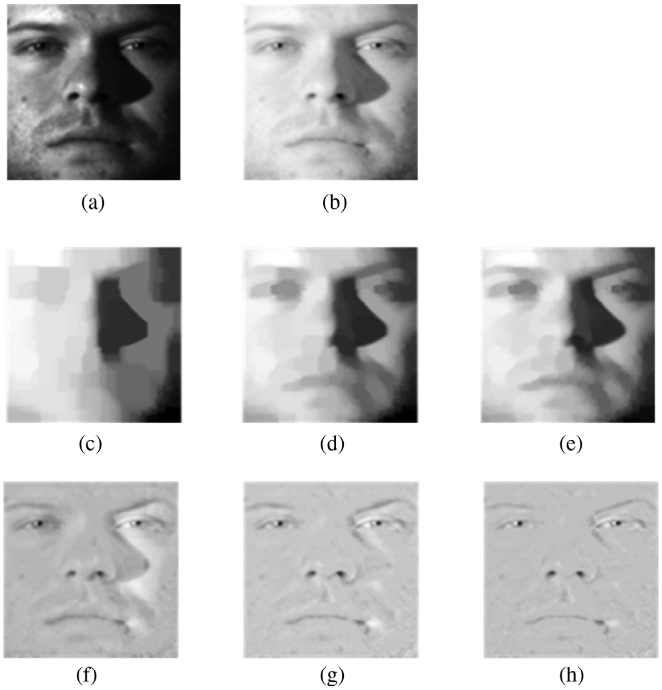

Figure 2. Results of the LTV illumination preprocessing method: (a) original image; (b) log-domain image; (c), (d), and (e) illumination components for λ equal to 0.15, 0.35, and 0.6, respectively; (f), (g), and (h) r components for λ equal to 0.15, 0.35, and 0.6.

preprocessing method applied to an example from the Extended YaleB facial database for different size parameters.

Figure 2 shows that λ determines the extent of the preprocessing. The images in (c) and (f) are the results using a smaller λ; the illumination components are very fuzzy and the reflection components retain more information about the face. The images in (e) and (h) are the results using a larger parameter; the illumination component is clearer, but the influence of illumination is significantly removed from the reflected image and some essential facial information is lost. To achieve the best effect with respect to the LTV illumination preprocessing method, smaller parameters should be chosen for images taken under good illumination conditions because we then retain more facial information. For images taken in dramatically different illumination conditions, a larger parameter will better remove the influence of extreme illumination conditions. This is the preliminary idea behind adaptive illumination preprocessing.

3.3 Adaptive Parameter Adjustment Model Based on LTV

To achieve an adaptive illumination preprocessing method based on LTV, we must adjust the parameter of the LTV model according to the illumination conditions. The adaptive illumination preprocessing method is shown in Fig. 3.

As shown in Fig. 3, we first evaluate the quality of the illumination quality using the IQI of the facial image. Then, we create the adaptive parameter adjustment model

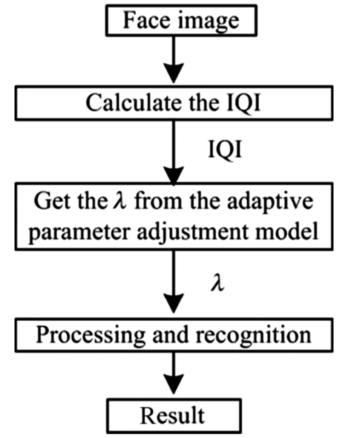

Figure 3. Flowchart of the adaptive illumination preprocessing method based on LTV.

based on LTV. This parameter adjustment model adjusts the LTV parameter according to the IQI. Finally, we finish preprocessing and send the results to the recognition method.

The adaptive parameter adjustment model is very important to the adaptive illumination preprocessing method based on LTV. The appropriate LTV parameter can be calculated for a facial image in any illumination condition. Section 2 showed that IQI is an excellent way to measure the illumination changes in a facial image. Additionally, λ is the key to determining the extent of the required preprocessing. So, the adaptive adjustment of LTV should combine IQI and λ. In this paper, we use the adaptive parameter model

$$\lambda = p(\mathrm{IQI}) \tag{6}$$

where IQI is the facial image IQI, λ is the LTV model parameter, and p is a function of IQI.

According to our analysis of Fig. 2, p can be speculated to be a monotone decreasing function of IQI. That is, a larger IQI should correspond to a smaller λ. Because the distribution of p is unknown, we used the following analysis of the training method to determine the distribution of p and develop the adaptive parameter adjustment model.

3.4 Training Method of the Adaptive Parameter Adjustment Model

To train the model, we need to know the distribution of the adaptive parameter adjustment function based on LTV. Here, we randomly chose 20 samples from the Extended YaleB face database, using positive images under varying illumination conditions for training. Additionally, all the facial images were adjusted to a size of 100×100 using bilinear interpolation.

3.4.1 Ranking the Whole Training Set Using IQI

To quantify the various illumination conditions and establish an experimental foundation for the adaptive

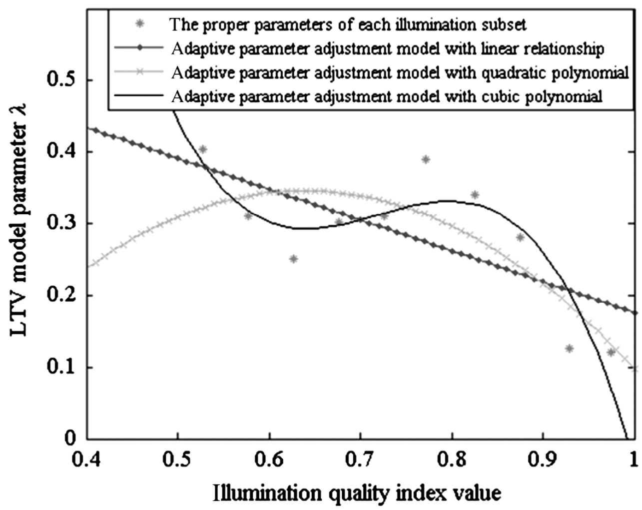

Figure 4. IQI values compared to optimal LTV parameter.

parameter adjustment model, we must rank the whole training set according to IQI. First, we calculated the IQI of 20×64 training images. Then, all images were divided into 20 illumination levels according to their IQI values (from 1 to 0). The IQIs of images belonging to illumination level 1 are in the range 0.95–1, the IQIs of images belonging to illumination level 2 are in the range 0.9–0.95, and so on. There were few images with IQIs less than 0.5, so we removed the low IQI images and worked with 10 illumination levels. After this categorization, the tests on each illumination level were very convenient.

3.4.2 Determining the Appropriate Parameter for Each Illumination Level

Adaptive illumination preprocessing based on LTV should result in the appropriate level of preprocessing for any illumination condition. According to our quantitative analysis of illumination conditions, we determined the appropriate parameter for each illumination level. These parameters provide guidance for the adaptive illumination preprocessing method. The steps to determine these parameters are as follows.

For an image of size 100×100, the LTV parameter's empirical value is between 0 and 1. So, we first ran the LTV illumination preprocessing on each illumination level with parameters between 0.01 and 1, and the calculated the recognition rate. Then, we determined the parameters of LTV for each illumination level that maximized the recognition rate. That is, we obtained the optimal LTV parameter for each illumination level. A scatterplot of the mean IQIs of each illumination level and the optimal parameters is shown in Fig. 4.

Figure 4 agrees with our analysis of the results shown in Fig. 2. That is, the optimal LTV parameter is smaller when the IQI is larger.

3.4.3 Adaptive Parameter Adjustment Model

The adaptive LTV parameter adjustment model in Fig. 4 confirms that a larger IQI requires a smaller LTV parameter. Therefore, we first used linear models in the adaptive parameter adjustment model. However, we found that the relationship is not linear, and a linear model did not improve the recognition rate. We next tried a nonlinear model. Using a quadratic polynomial model, we found that when the IQI was large the models are a good fit but they were not when the IQI was small. Finally, based on extensive experimental results, we found that a cubic polynomial model can effectively fit the adaptive LTV parameter adjustment model, that is,

$$\lambda = a\mathrm{IQI}^3 + b\mathrm{IQI}^2 + c\mathrm{IQI} + d \tag{7}$$

where $a\mathrm{IQI}^3 + b\mathrm{IQI}^2 + c\mathrm{IQI} + d$ is a polynomial model; IQI is the facial illumination quality index; a, b, c, d are the model coefficients obtained using a curve fitting method; and λ is the LTV parameter.

The adaptive LTV parameter adjustment model is shown in Fig. 4 as the fitted curve, and we can see that it accurately fits the scatterplot. This completes the core work of the proposed adaptive illumination preprocessing method that adjusts the LTV parameter according to illumination conditions.

4. Experiment and Analysis

We validated the proposed method's performance by comparing it with classical facial recognition illumination preprocessing methods such as HE [8], Log [1], GIC [15], SQI [15], MSR [13], S&L [19], LTV [18], and the method in [24]. We applied the methods to the CMU-PIE and Extended YaleB face databases, which are commonly used to evaluate the performance of illumination-invariant face recognition methods. However, many illumination preprocessing methods (including the proposed method) have achieved a 100% recognition rate when applied to the CMU-PIE face database. Therefore, we only present the experimental results on the Extended YaleB face database. Because we trained the proposed method using 20 samples from the Extened YaleB face database, we tested the method using the remaining 18 samples. For each sample, only one front illumination image was selected as a reference image, and the others were used as probe images. To compare the abilities of the various methods, we also applied the template matching method, which is sensitive to illumination conditions. In this method, the angle cosine distance is used to measure the similarity between facial images, and a nearest neighbor classification is used for the recognition step. In order to avoid the accidental error caused by the single experiment, we repeated the experiment 50 times and took the mean and variance of the experimental results. Every time, we selected 20 random samples for training, and the remaining 18 samples for testing. Finally, we calculated the average recognition rate of each method. The results are given in Table 1.

Table 1
Parameters of Various Illumination Preprocessing Methods

Method	Parameters
Log	discardNr = 50
GIC	$\gamma = 7.0$
MSR	$\kappa = [5,9,15]$
SQI	$\kappa = [5,9,15]$
LTV	$\lambda = 0.24$
S&L	$\lambda = 0.24$, discardNr = 50
[24]	IQI = 0.974
Proposed	$a = -6.3059$, $b = 10.5655$, $c = -5.4556$, $d = 1.2376$

In Table 1, κ represents the size of the Gaussian window, λ represents the regularization parameter in LTV, discardNr represents the number discrete cosine matrix coefficients, and γ is the parameter gamma transform in GIC. In [24], an IQI threshold of 0.974 was used; if an image had an IQI larger than this we did not apply image processing to avoid the negative effects brought by processing. The parameters of the proposed method depended on the different training samples, so Table 1 gives the values of one of the training results. Finally, we calculated the average recognition rate of each method, as shown in Table 2.

Table 2 shows that LTV and S&L [15] are excellent illumination preprocessing methods, and achieved high recognition rates that were better than those for HE [8], MSR [13], and the other methods. Compared with LTV, the method in [24] abandons preprocessing for high IQI values, which to some extent avoids the negative effect of the illumination preprocessing. Therefore, it only improved the recognition rate of Subset 1, which were taken under extreme illumination conditions. So, the method in [24] can only be regarded as a locally adaptive illumination preprocessing method with great limitations. Compared with LTV, the proposed method improved the recognition rate in almost each subset; the recognition rate of Subsets 1, 3, 4, and 5 increased by 2%, 1%, 2%, and 2.8%, respectively. Thus, the results imply that the proposed method can more effectively adapt to a wide range of illumination conditions, and uses an optimal level of illumination preprocessing to improve the face recognition rate.

5. Conclusion

Traditional illumination preprocessing methods apply the same preprocessing levels to various illumination conditions, and therefore have limitations. In this paper, we proposed an adaptive illumination preprocessing method. The proposed method models the adaptive LTV parameter adjustment according to the illumination conditions, so it preprocesses the facial images according to their unique illumination conditions. Our extensive simulation results demonstrated that the proposed method can effectively improve the face recognition rate under various illumination conditions. Additionally, the method can be applied to the LTV model, and also to MSR, SQI, and other classical illumination preprocessing methods. These illumination preprocessing methods in combination with the proposed method can optimally adjust the parameter and improve the recognition rate. We have only verified the proposed method on the Extended YaleB and CMU-PIE face databases. However, there are many other face databases such as the MIT-CBCL [25] and NLPR [26] face database. Our future work will focus on applying the proposed method to a real condition.

Table 2
Recognition Rates of Various Methods Applied to the Extended YaleB Face Database on Five Subsets of Data

Method	Subset 1	Subset 2	Subset 3	Subset 4	Subset 5
Unprocesse d	1(0)	0.986(0.009)	0.587(0.067)	0.185(0.031)	0.082(0.013)
HE	1(0)	0.964(0.023)	0.563(0.072)	0.232(0.059)	0.282(0.034)
Log	1(0)	0.993(0.008)	0.670(0.055)	0.376(0.075)	0.390(0.048)
GIC	0.995(0.008)	0.990(0.008)	0.682(0.059)	0.485(0.075)	0.572(0.053)
MSR	0.969(0.027)	0.983(0.024)	0.841(0.03)	0.710(0.046)	0.897(0.031)
SQI	0.928(0.024)	1(0)	0.952(0.008)	0.939(0.024)	0.933(0.075)
LTV	0.978(0.027)	1(0)	0.925(0.026)	0.919(0.013)	0.916(0.034)
S&L	0.897(0.008)	1(0)	0.877(0.013)	0.876(0.024)	0.864(0.053)
[24]	0.990(0.020)	1(0)	0.925(0.026)	0.919(0.013)	0.916(0.034)
Proposed	0.998(0.050)	1(0)	0.935(0.022)	0.939(0.020)	0.944(0.036)

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Biographies

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