The Improved Multi-scale Retinex Algorithm and Its Application in Face Recognition

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Abstract: In this paper an improved multi-scale Retinex algorithm is studied to solve the insufficiency that the traditional multi-scale Retinex algorithm is incapable of non-uniform illumination images. Before being processed by the multi-scale Retinex algorithm, the given images are preprocessed by a nonlinear transformation to make the illumination of images tends to uniform. Besides, the improved algorithm is combined with PCA and LDA algorithm and apply for face recognition to identify the face images under complex illumination. Simulations show that the improved algorithm has a better ability for various illumination, and it increases the recognition rate under complex illumination.

Key words: face recognition; complex illumination; multi-scale Retinex; nonlinear transformation.

1 INTRODUCTION

In pattern recognition field, much attention has been attracted to face recognition in recent years, and illumination of face images as a difficulty has attracted researchers to proposed many methods to solve it[1][2]. Recently, the Retinex algorithm which was originally proposed by Land [3] has been used to process the illumination of face images and obtains a good performance [4] [5]. Jobson et al. evolved Land's theory to single-scale Retinex (SSR) and multi-scale Retinex (MSR)[6][7]. Compared with SSR, MSR which is defined as a weighted sum of several SSRs is more effective in both local contrast enhancement and dynamic range compression [8]. The Retinex theory divides an image into illumination component and reflectance component, the former represents the light information of the image, while the latter shows what the object originally looks like. Through eliminating the illumination from the image and reserving the reflectance, the original appearance of the object can be restored and the influence of illumination can be removed. However, the Retinex theory assumes the light changes uniformly, so it performs well with uniform illumination images, but it is incapable of non-uniform illumination images [9] [10]. To solve this problem, we propose an improved MSR algorithm with a nonlinear transformation in this paper. The given images are preprocessed by the nonlinear transformation which can improve the pixel values in low-light areas and make the illumination of the images tends to more uniform, then the MSR algorithm works with the preprocessed images. Such improvement has a better ability to smooth the light of images and reduce the influence of non-uniform illumination which overcomes the shortage of the traditional MSR algorithm.

Principal component analysis (PCA) and linear discriminant analysis (LDA) are very popular in face recognition. PCA can reduce the dimensions of the face samples by mapping them into a subspace named Eigenface space [11]. LDA can get a subspace that best discriminates different face classes by maximizing the between-class scatter matrix, while minimizing the within-class scatter matrix [12]. However, the dimensions of samples cannot be too large because LDA algorithm requires the dimensions of samples must be smaller than the number of samples. So, the combined algorithm of PCA and LDA has been researched in many literatures [13] [14]. In this paper, we apply the improved MSR algorithm into the combined algorithm of PCA and LDA for face recognition. First, remove the influence of light of given images by the improved MSR algorithm, then identify the processed images by PCA and LDA algorithms. Such an approach overcomes the drawback that PCA and LDA are sensitive to light. In the experiments, we also compare the applications of the traditional MSR algorithm and the improved MSR algorithm, and the results indicate that the improved one is more effective to process complex illumination images.

2 MULTI-SCALE RETINEX THEORY (MSR)

According to Retinex theory, a given image S can be regarded as a combination of illumination image L that represents the light information and reflectance image R that represents the original attributes of the image. Then each point (x,y) in the image can be represented as:

$$S(x,y)=R(x,y)\bullet L(x,y) \tag{1}$$

Such decomposition has the ability to remove the lighting effects from the given image by reserving the reflectance. Usually, for convenience of calculation, the above formula is always converted to logarithm domain:

$$\log S(x,y) = \log R(x,y) + \log L(x,y) \tag{2}$$

It is not easy to solve $R(x,y)$ from above equation directly. But the illumination image L can be estimated from S through a low-pass filter because the assumption that the illumination changes uniformly donates the illumination image L corresponds to the low-frequency part. In single-scale Retinex (SSR) algorithm, R is estimated by following equations.

$$\begin{cases} \log R(x,y) = \log S(x,y) - \log[F(x,y) * S(x,y)] \\ F(x,y) = \lambda \exp(-\frac{x^2+y^2}{c}) \\ \iint F(x,y) = 1 \end{cases} \tag{3}$$

where $F(x,y)$ is a Gaussian function which is used as the low-pass filter, $*$ represents convolution, λ is a coefficient, c is an important parameter named surround scale. SSR algorithm cannot get a balanced result because large c leads to good dynamic range compression but poor local contrast enhancement, while small c leads to the opposite result. So multi-scale Retinex (MSR) algorithm which is a weighted sum of several SSRs was proposed, which can be described as following equations.

$$\begin{cases} \log R(x,y) = \sum_{i=1}^{n} \omega_i \{\log S(x,y) - \log[F_i(x,y) * S(x,y)]\} \\ F_i(x,y) = \lambda_i \exp(-\frac{x^2+y^2}{c_i}) \\ \iint F_i(x,y) = 1 \end{cases} \tag{4}$$

where n donates the number of surround scales, $F_i(x,y)$ is the i-th filter, ω_i is the weight corresponds to $F_i(x,y)$ and $\sum_{i=1}^{n} \omega_i = 1$. Generally, to get a balanced result between local contrast enhancement and dynamic range compression, take $n=3$, $\omega_1=\omega_2=\omega_3=1/3$ and $c_1=15, c_2=80, c_3=120$.

3 IMPROVED MSR ALGORITHM

The assumption of Retinex theory cannot be always met, there are always non-uniform illumination images in reality, such as side-light images, the MSR algorithm is helpless to this kind of images. So it is necessary to preprocess the images before using MSR. In this paper a nonlinear transformation defined as formula (5) is use for preprocessing.

$$S_o(x,y) = \min + (\max - \min) \cdot \left(\frac{S_i(x,y) - \min}{\max - \min} \right)^{\gamma} \tag{5}$$

S_i and S_o represent the given image and preprocessed image respectively, " min " and " max " are respectively the maximum pixel value and the minimum pixel value of S_i, $\gamma \in [0,1]$. Figure 1 shows some curves corresponds to different values of γ.

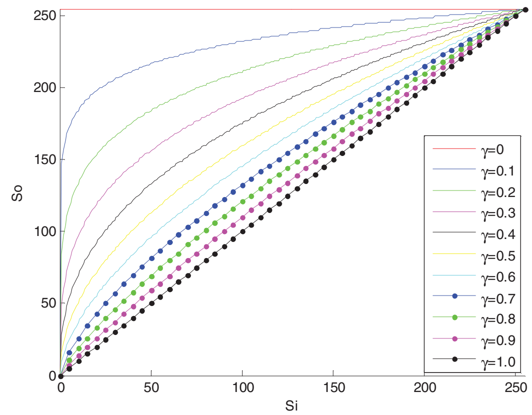


Figure 1. Function curves corresponds to different values of γ

The figure shows that when γ is smaller, the low pixel area is more stretched and high pixel area is more compressed. And it is a linear transformation that outputs equal to inputs when $\gamma=1$, all of pixels are compressed to the maximum value when $\gamma=0$. A lot of experiments indicate that the results are acceptable when $\gamma \in [0.3, 0.4]$.

Such transformation has many advantages. First, the offset of the minimum pixel value can retain the dynamic range of pixels. Second, in the minimum value nearby, narrow range of inputs are mapped to wide range of outputs, which leads to the local contrast enhancement of low-light area. The most importance is that the pixels value in low-light area are improved which makes the illumination uniform changes, then the MSR algorithm can get more effective results. So, for a given image, we preprocess it with the Formula (5) before using MSR algorithm.

4 THE APPLICATION OF IMPROVED MSR IN FACE RECOGNITION

4.1 The combination of improved MSR and PCA and LDA

Principal component analysis (PCA) and linear discriminant analysis (LDA) are common used in face recognition, they both need to convert the face images to vectors. PCA algorithm tries to reduce dimensions of samples by mapping them to the Eigenface space that spanned by the eigenvectors of sample covariance matrix. LDA algorithm tries to find a set of linear transformation to map the samples to a subspace that discriminates different classes by maximizing the between-class scatter matrix, while minimizing the within-class scatter matrix, so it is suitable for face recognition in theory.

Samples for LDA cannot have a large dimensions because the algorithm requires the dimensions of samples must be smaller than the number of samples, so the combined algorithm of PCA and LDA was proposed. Usually, the PCA algorithm is used to reduce the dimensions of samples, then the LDA algorithm work in the Eigenface space. In this paper, the improved MSR algorithm is applied to the combined algorithm to solve the problem that PCA and LDA have a poor robustness for complex illumination.

4.2 Steps of face recognition

The steps of face recognition in this paper is listed.

Step 1. Preprocess the given image S_i with the formula (5).

Step 2. Process the preprocessed image S_O by the MSR algorithm.

$$\log R(x,y)=\sum_{i=1}^{n}\omega_i\{\log S_O(x,y)-\log[F_i(x,y)*S_O(x,y)]\}$$

Step 3. Convert the processed image R to a vector x .

Step 4. Define $\{x_i\}$ as the set of training samples (the samples in the set have been processed by the improved MSR algorithm),

Step 5. Compute the transform matrix V of Eigenface subspace by PCA algorithm from $\{x_i\}$.

Step 6. Compute the transform matrix W by LDA algorithm.

Step 7. Define d_i as

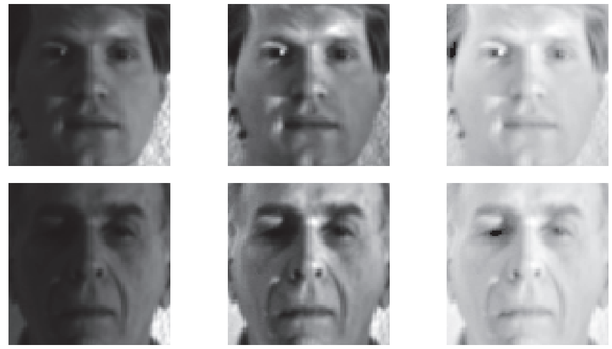
$$d_i=\left\|W^T V^T\left(x-\overline{x_i}\right)\right\|$$

where $\overline{x_i}$ is the mean of the i-th class. The given image x belongs to the class that minimize d_i ,

5 SIMULATIONS AND RESULTS

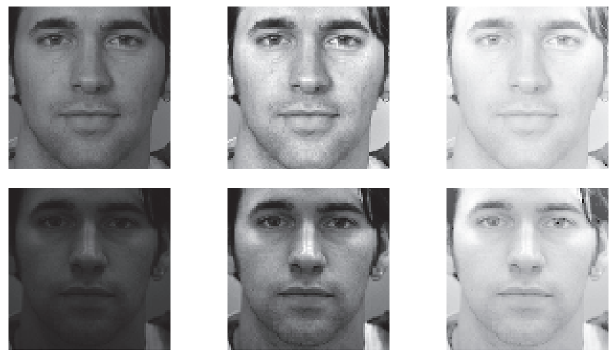
5.1 Simulations of the improved MSR algorithm

In this section, some experimental results are provided to demonstrate the effectiveness of the proposed algorithm. The simulation results of MSR and improved MSR are shown in Figure 2 and Figure 3. Figure 2 shows a group of sigh-light images and their processed results by MSR and improved MSR algorithm. It is obvious that the side light still affects the images that processed by MSR algorithm. The images processed by the improved MSR algorithm not only improve the brightness, weaken the influence of the side light, but also show more details of the low-light area. Figure 3 shows a group of images under different illumination and their processed results by MSR and improved MSR algorithm. We can see that the brightness in the images that processed by MSR is still diverse, and the images that processed by improved MSR have the similar brightness to each other. Thus the simulation results demonstrate that the improved MSR algorithm has a better ability to smooth the light of the image and reduce the influence of various illumination of images.



(a). original images (b). processed by MSR (c). processed by improved MSR

Figure 2. Side-light images



(a). original image (b). processed by MSR (c). processed by improved MSR

Figure 3. Images under different illumination

5.2 Simulations of face recognition

In order to verify the effect of the algorithm proposed in this paper, we did simulations on FERET face database, and compared the results of three recognition methods, including the combined algorithm of PCA and LDA, the traditional MSR algorithm and the improved MSR algorithm (the latter two algorithms both work with PCA and LDA). Table 1 show the simulation results.

Table 1. Simulation results

Method / Recognition rate / Samples for training	PCA&LDA	MSR&PCA &LDA	Improved MSR&PCA &LDA
4	54.00%	56.50%	58.33%
5	50.5%	67.50%	73.25%
6	9.50%	61.50%	77.00%

As the table shows, in the first method, the more samples, the lower recognition rates. This is because of the structure of FERET database. There are 200 groups of face images in the database, and there are 7 images for different pose and illumination in each group. The Figure

4 shows a group of images in the database.

Figure 4. A group of images in FERET database

Obviously, the seventh image is darker than the former six images, and in each experiment we choose four, five or six images from the former six as training samples and the seventh image is always test sample. The results indicate that PCA and LDA methods have a poor robustness for illumination. Though the second method has a better recognition rate than the first method, the result of six samples is still worse than the result of five samples. So the traditional MSR algorithm has a limited capacity to reduce the influence of complex illumination. The recognition rate of third method is much better than the former two methods, besides, the more samples, the higher recognition rate. So the third recognition method has a better robustness for complex illumination. The simulations demonstrate that the improved MSR algorithm is more capable to remove the influence of illumination more effectively.

6 CONCLUSION

In this paper an improved MSR algorithm is proposed to remove the influence of complex illumination of images. In the proposed algorithm, a nonlinear transformation is used to preprocess the images to smooth the illumination. Also, the improved MSR algorithm is applied for face recognition with PCA and LDA to enhance the robustness of illumination of recognition methods. In the experiments, the improved MSR algorithm is more capable to smooth the light and reduce the influence of complex illumination than the traditional one, and the recognition method with improved MSR algorithm is more robust to illumination and has a better recognition rate. The results and the comparisons indicate the improved algorithm has a better performance as it overcomes the shortage of the traditional method.

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