Image Enhancement Technique using Adaptive Multiscale Retinex for Face Recognition Systems

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Abstract. Various illumination effects in an image are one of the states of difficulty that should be solved in order to get a satisfactory result in face recognition task. The inhomogeneous intensities of the image has led to many plans and algorithms to devastate the cause and next to eliminate the illumination. The focus of this paper is to enhance the image by reducing illumination effects; employing a preprocessing step i.e. adaptive multiscale retinex as the illumination correction method before accomplishing the recognition task. The performance of this method is evaluated using the Yale database and has lower equal error rate compared with single scale retinex and conventional multiscale retinex.

1 Introduction

In face recognition, usually there are some inconsistencies between the real scenes and the training set images. One of them is illumination variations such as shadow, blur, dark and noise occurring in the images. Sometimes this can cause degradation in the algorithm to recognize the face image. In this paper, we want to reduce the unwanted effects in face images by applying adaptive multiscale retinex as a preprocessing step. Multiscale retinex was initially used to provide stability in color images; however it is also competent to be used in gray scale images.

Lightness and color uniformity refer to wide range of intensity and spectral illumination variations [1]. Multiscale retinex is formed from the retinex theory by Edwin Land [2]. Land proposed the idea of retinex as a model of lightness to measure the lightness response in an image.

However Land did not apply the model to image enhancement algorithm, but this is done by Jobson where they define the properties of the surround/center retinex function [3]. The characteristic they describe is single scale retinex when they performed logarithmic after the surround function. They also apply ‘canonical’ gain offset to the retinex output to clip certain parts of the highest and lowest signal excursion. However, single scale retinex can either provide dynamic range

Ishak K., Abdul Samad S., Hannan M. and Mohd Sani M. (2009).
Image Enhancement Technique using Adaptive Multiscale Retinex for Face Recognition Systems.
In *Proceedings of the 5th International Workshop on Artificial Neural Networks and Intelligent Information Processing*, pages 43-49
DOI: 10.5220/0002262600430049

compression on small scale, or tonal rendition for large scale image. This limitation expands single scale retinex to a more balanced method that is multiscale retinex.

After that, another characteristic of multiscale retinex were found where other than dynamic range compression, multiscale retinex purposes are to replicate tone in an image in order to reduce its dependencies in lighting conditions and improved spatial resolution[4]. So we use this characteristic in this paper to lessen illumination effects in order to obtain controlled lighting condition in a face image. We modify the present multiscale retinex by including histogram shifting and adaptive histogram equalization to the original algorithm as to have a more uniform face image contrast than the original method. The detail of this proposed method will be discussed in section 3. Before that, section 2 will cover the original theory of multiscale retinex. Section 4 will describe the experimental results and lastly is the conclusion in Section 5.

2 The Original Multiscale Retinex

The original multiscale retinex essentially measure the intensity of an image and estimate the illumination from the proportion of the local image mean intensity value. By applying Gaussian filter, the image is smoothed at different weight and size in order to find the mean of the image. To obtain the retinex output, the filtered image is divided using the illuminated image (input). Then, logarithmic function is done to compress dynamic range of images with large variations in pixel value [5] before the image is reconstructed again using additive function.

The original multiscale retinex algorithm is obtained from single scale retinex [4] as in (1):

$$R(x,y)=\log I(x,y)-\log[F(x,y)*I(x,y)] \quad (1)$$

where I(x,y) is input image, R(x,y) is retinex output, F(x,y) is the Gaussian surround function. Symbol * denotes convolution. Gaussian surround function is given by:

$$F(x,y)=K.e^{-(x^2+y^2)/c^2} \quad (2)$$

where c is Gaussian shaped surrounding space constant. The value of c is related to visual angle in the direct observation which is determined through experiment. K is selected such that:

$$\iint F(x,y)dxdy=1 \quad (3)$$

Until this stage the single scale retinex would only provide tone reproduction and dynamic range compression at certain scale in an image. The image would have only one of the important characteristics. Thus, to overcome this limitation, superposition of different scale at certain weight would solve this problem as shown in (4), where

N is number of scale, where R_{ni} is different scale of single scale retinex. ω_n is the weight of each single scale retinex with equal value.

$$R_{MSRi}=\sum_{n=1}^{N}\omega_n R_{ni} \tag{4}$$

3 The Adaptive Multiscale Retinex

After applying the original multiscale retinex, we found that the image was too dark. This meant that the image brightness and contrast needed to be altered. Thus we modified the algorithm by applying a recombination with the original image. According to [6], a method need to be applied to restore the information in different regions to smoothen the global contras in the image according to which region is darker or brighter. The information here is, different intensity in different regions in the original picture. For this reason, recombination is needed to restore the information as in (5):

$$R_{MSRi} = \sum_{n=1}^{N}\omega_n R_{ni}+\omega_{original}\cdot\log(\text{original})\,. \tag{5}$$

After recombination with weighted original picture, adjustment is made on the histogram by performing a constant shift which helps improve the entire global brightness of the image. To shift the histogram is a simple task, where in the range of 0-255 the image pixels should be. In order to allocate the pixels in the range, we set the initial maximum pixel (MinVal) as 0, and the minimum pixel (MaxVal) as 255. Then we evaluate the entire image pixels one by one and update the new value (NewVal) using (6). Prior to that, every pixel value (PixVal) has to be tested whether it is higher than the MaxVal or lower than the MinVal. If the value is higher, then the MaxVal will be the PixVal value and the similarly, MinVal if the value of PixVal is lower than MinVal. These values are needed to find the new value which is compute from

$$\text{NewVal} = \left[\frac{\text{Pixval-MinVal}}{\text{MaxVal-MinVal}}\right] * 255\,. \tag{6}$$

Next, we execute a local image enhancement technique that divides the image into rectangular blocks. Usually how many blocks should be used is determine through experiments. First, obtain the cumulative density function of the small region histogram. Then the centre pixel of the region is equalized (histogram equalization) and moved to the adjacent pixel in the rectangular region. This process is called adaptive histogram equalization (AHE) [7].

Overall, the adaptive multiscale retinex algorithm is shown as in figure 1.

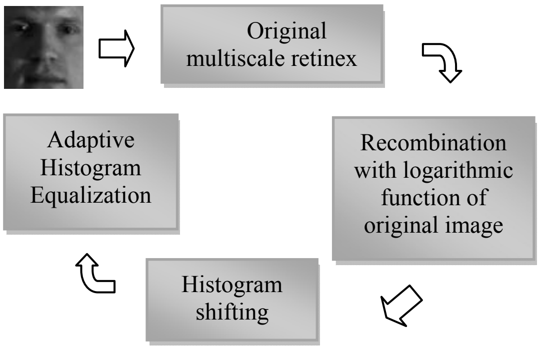

Fig. 1. The adaptive multiscale retinex flowchart.

4 Experimental Results

We evaluate the performance of the preprocessing methods using Eigenface [8] as the feature extractor while Euclidean distance is used for the matching purpose. We also implement a fusion of Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) [9] for data reduction. The performance is evaluated using well known benchmarking measures for biometrics system i.e. Equal Error Rate (EER) [10]. To compute EER, two components must be determined. The first is false acceptance rate (FAR), when the impostor is falsely regarded as the client. Another one is false rejection rate (FRR), when the client is falsely regarded as the imposter. Here the client is the authorize person in the face recognition system. The EER is the cross-over value where FAR and FRR coincide.

The dataset we use to evaluate the algorithms is Yale [11], which contains 165 grayscale images of 15 individuals. There are 11 images per subject, one per different facial expression or configuration. The 11 images show various extreme illuminations and pose criteria. We randomly selected 5 images from each subject to be the training sample and 5 images of each subject as the testing sample. Our experimental face condition is cropped face images. The size of all images is standardized to 50x60.

The experiments are done using grayscale images as the inputs. Three methods are compared, i.e., single scale retinex, multiscale scale retinex and the adaptive multiscale retinex. Table 1 shows the EER for these methods where we can see that the EER for the adaptive multiscale retinex is the lowest compared to the original multiscale retinex and single scale retinex.

Table 1. EER comparison of three methods.

Method	EER (%)
Single Scale Retinex	11.87
Multiscale Retinex	10.33
Adaptive Multiscale Retinex	10.27

The EER results correlate with the output images of the three methods. To illustrate, we choose 4 faces from the database which have been illuminated with different lighting conditions: cast shadow, attached shadow, specular reflection and diffuse reflection [12]. The lighting conditions are shown in figure 2. Figure 3 illustrates the outputs for all three methods. For face number 1, only the adaptive multiscale retinex is able to eliminate the diffuse reflection. For face number 2, there are specular reflection and strong cast and attached shadow, where the adaptive algorithm is capable in removing the specular reflection. The condition in face number 3 is the same as number 1. Face number 4 contains cast shadow, specular and diffuse reflection. The adaptive multiscale retinex is able to remove all the lighting distraction on the face image, except the cast shadow.

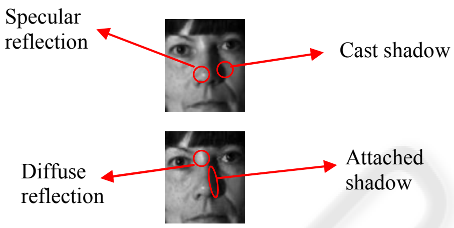

Fig. 2. Different lighting conditions of a face.

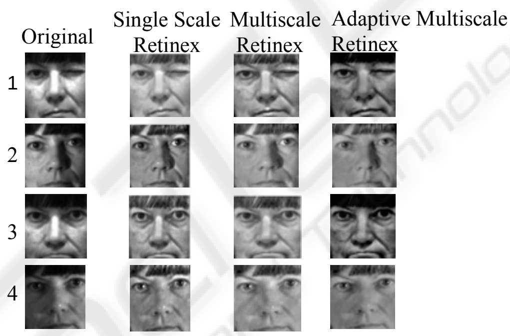

Fig. 3. The image outputs using three methods for person 1, 2, 3, and 4.

Figure 4(a), (b), (c) and (d) show the output histograms for face images 1, 2, 3, and 4 before and after applying the adaptive multiscale retinex. For all the histograms, the upper figure indicates the histogram before and the lower figure is the one after. All the histograms show more balanced tone representation in gray scale values. The histograms centred at the middle show ordinary conditions with peaks and gradually tapering off on the left and right sides of the histogram. This proves that the method is able to reduce broad tonal range from the original face image.

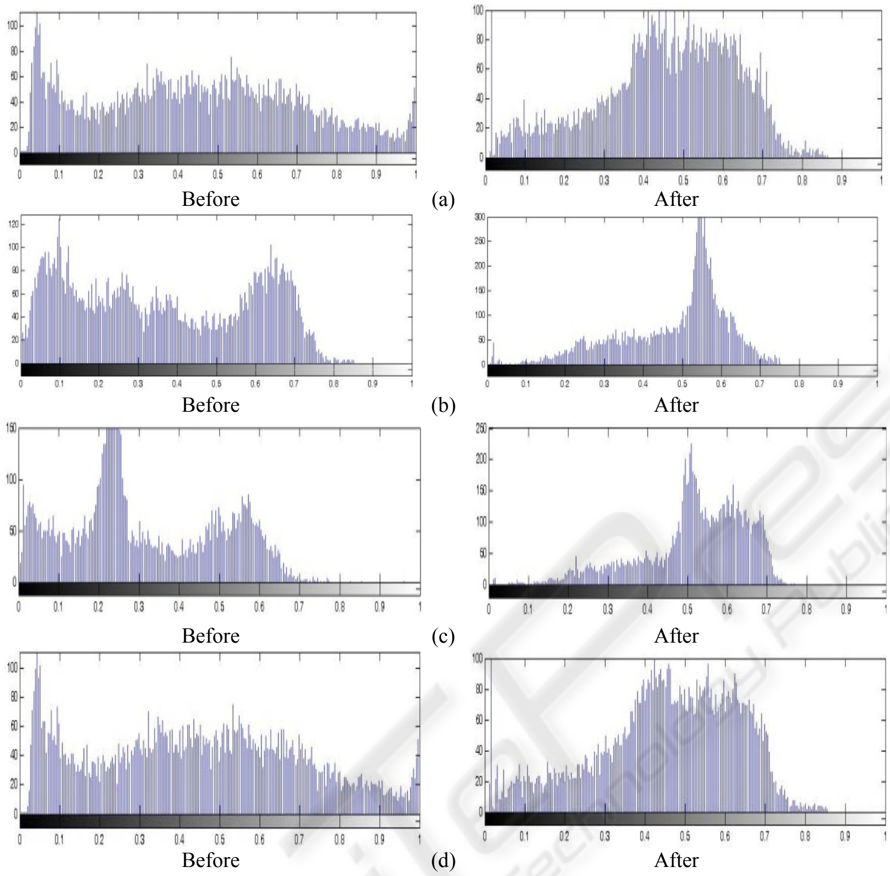

Fig. 4. (a), (b), (c), (d). The histogram before pre-processes (the original image) and after pre-processed with adaptive multiscale retinex for person 1, 2, 3 and 4.

5 Conclusions

In this paper, an adaptive multiscale retinex algorithm is presented. The purpose is to remove illumination appearances. This is achieved by modifying the multiscale retinex algorithm with adaptive histogram equalization and histogram shifting. The performance of this method is tested using the Yale dataset and shown in terms of EER rate and output comparisons with single scale retinex and conventional multiscale retinex.

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