Research on preprocessing algorithm based on complex illumination condition

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Abstract. In the field of image processing, complex illumination conditions have a serious impact on the accurate recognition of targets. Pre-processing complex illumination before face recognition can improve the accuracy of face recognition. In this paper, the Light is preprocessed by image enhancement algorithm and illumination invariant feature extraction algorithm based on Lambertian illumination model. The image enhancement algorithm achieves the purpose of preprocessing by adjusting the gray scale, and the illumination invariant feature algorithm achieves the purpose of preprocessing by extracting the features of the face. Finally, the advantages and disadvantages of the two types of algorithms are compared and analyzed through experimental results.

1. Introduction
Complex illumination has a serious impact on image recognition, in addition to face recognition, lighting also affects other image recognition. When the value of the digital instrument is recognized, the instrument will be reflective because the illumination is too strong, thus causing the recognition result to be wrong. The result also will be inaccurate because the light is too weak. It can be seen that pre-process of complex illumination has become an urgent problem in image processing.

2. Image Enhancement Algorithm

2.1. logarithmic transformation
The dark pixel value portion of the face is expanded by logarithmic transformation, and the high gray level value of face image is compressed to reduce the influence of illumination. Its formula is as follows.

\[
s = c \cdot \log_{v+1} (1 + v \cdot r) \quad r \in [0, 1]
\]

Where \( c \) is a constant; the base of the logarithmic transformation is \( v+1 \); \( r \) is the normalized input value, the input range is \([0, 1]\); \( s \) is the output value after the corresponding pixel is transformed, and the output range is also \([0, 1]\);

In order to verify the method, any one of Extended Yale B's face images in Subject1, Subject2, Subject3, Subject4, and Subject5 is randomly selected for illumination preprocessing. The selected original image is shown in Figure 1(a).
Figure 1 The effect pictures of Logarithmic transformation Processing

It can be seen from Figure 1 that the larger the v, the greater the brightness, so choosing the appropriate v can reduce the effect of illumination.

2.2. Gamma transform
Gamma transforms are primarily used for image correction, which maps narrower or wider ranges of regions to narrower or wider regions, respectively\(^\text{[2]}\). Its formula is as follows.

\[
S_{c \gamma} = c \cdot r^\gamma
\]  

(2)

In the formula, c takes a normal number; \(\gamma\) is a gamma coefficient; its input and output are both [0, 1].

In order to verify the gamma correction, the original image will be processed by setting c to 1 and transforming the value of \(\gamma\). The resulting effect is shown in Figure 2.

Figure 2 The effect pictures of Gamma transformation processing

2.3. Histogram equalization
Grayscale processing of the image will result in uneven distribution of the histogram, and the overall gray level distribution will be concentrated, resulting in the target information not being prominent. After the histogram equalization, the pixels of the image can be evenly distributed over the entire possible gray level, thereby enhancing the grayscale contrast of the image\(^\text{[3]}\).

Let the sum of the pixels of the image be \(n\), and divide the L gray values. Where \(n_k\) is the frequency at which the kth gray value appears, and the probability that the kth gray value appears is \(p(r_k) = n_k / n\) \((0 \leq r_k \leq 1, k = 0,1,2,\ldots,L-1\) . The formula is as follows.
As shown in Figure 3, Figure (a) is an original image with severe illumination, and Figure (b) is an effect diagram after histogram equalization. It can be seen from the comparison that the histogram equalization can reduce the illumination influence, thereby improving image recognition rate.

\[ s_k = T(r_j) = \sum_{j=0}^{k} p(r_j) = \sum_{j=0}^{k} \frac{n_j}{n} \]  (3)

3. Lambert Illumination Model
The Lambertian illumination model describes the relationship between the gray value of a pixel of an imaged object and the incident light source that illuminates this pixel\(^{[4]}\). The typical Lambertian illumination model is shown in (4) below.

\[ I(x, y) = \rho(x, y)n(x, y)^T \cdot s(x, y) \]  (4)

Where \( I(x, y) \) denotes the image of the target object; \( \rho(x, y) \) denotes the diffuse reflection coefficient of the surface of the target object; \( n(x, y)^T \) denotes the surface shape of the target object, that is, the normal vector of the pixel point \((x, y)\); \( s(x, y) \) represents the point light source, whose size is equivalent to the light intensity of the light source and can be changed arbitrarily.

In the Lambertian illumination model, let \( \rho \), and bring this formula into Equation (4), that is, \( I(x, y) \) can be expressed as follows.

\[ I(x, y) = R(x, y)L(x, y) \]  (5)

3.1. Retinex Theory
Retinex algorithm is divided into single-scale Retinex algorithm (SSR) and multi-scale Retinex algorithm (MSR). The "multi-scale" in MSR means that \( k \) different Gaussian filters are selected, and the size of each filter is different. The purpose of multi-scale is to reduce the "halo" phenomenon\(^{[5]}\). The mathematical expression of the MSR algorithm is shown in equation (6).
\[ R(x, y) = \sum_{i=1}^{k} w_i \times \{ \log S(x, y) - \log [S(x, y) \ast F_i(x, y)] \} \]  \hfill (6)

Where \( k \) is the number of Gaussian kernel functions, when \( k = 1 \), the MSR can be considered as SSR; \( w_i \) represents the weight. The effect pictures of multi-scale Retinex on face image preprocessing is shown in Figure 5.

![Figure 5 The effect pictures of Retinex algorithm processing](image)

It can be seen from the figure that the MSR algorithm can effectively remove the influence of illumination and extract the invariant features of face illumination. The "halo" phenomenon occurs at the intersection of the light and dark of some images. This is because the Gaussian low-pass filter used in Retinex theory can not estimate the illumination information well in the transition area, which leads to the appearance of "halo" phenomenon in the transition region of strong light shadow.

3.2. Dynamic Morphological Quotient Image (DMQI)

Morphological image processing has edge-preserving properties and is widely used in image denoising\(^6\). Dynamic morphological quotient images are proposed based on morphological quotient images. The mathematical expression of the DMQI algorithm is shown in equation (7).

\[
DClose(x, y) = \begin{cases}
Close'(x, y) & \text{if } \alpha \cdot Close'(x, y) > \alpha \cdot Close'(x, y) \\
Close''(x, y) & \text{if } \beta \cdot Close'(x, y) > \beta \cdot Close'(x, y)
\end{cases}
\]  \hfill (7)

Where \( \alpha \) and \( \beta \) are feature scale parameters, and \( \alpha > \beta > 1.0 \); \( l, m \) and \( s \) represent the template size, and \( l > m > s > 1 \).

If \( a > b \) indicates that the gray value of pixel \( x \) at the boundary of eyebrow, eye, mouth or the change of light intensity varies widely, and the calculation result of the large size template is greatly different from the calculation result of the small size template. Therefore, large size templates are preferred to maintain features. If \( c > d \) indicates that the pixel point \( y \) is in a smooth area (such as the cheek and forehead), and the area is uniformly illuminated, the gray value of the pixels in these areas changes little. In this case, a small-scale closed operation should be preferred.

The effect pictures of the DMQI algorithm is shown in the following Figure 6.

![Figure 6 The effect pictures of DMQI algorithm processing](image)

4. Experimental Verification and Result Analysis

In order to verify the influence of the illumination enhancement algorithm and the illumination invariant feature extraction method based on the Lambert model on the face recognition under complex illumination conditions, Subject 1 and Subject 5 of Extended Yale B are selected as the training set. The remaining subsets are used as test sets. The training set Subject 1 and Subject 5 respectively have 266, 722 face images, and the test sets Subject 2, Subject 3, and Subject 4 have 456, 456, and 532 face images, respectively\(^7\). From the perspective of recognition accuracy, the traditional image enhancement algorithms, such as logarithmic transformation, gamma correction and histogram equalization, were
compared with multi-scale retinal model (MSR) and dynamic morphological quotient image (DMQI) illumination invariant feature extraction algorithms.

Table 1 Recognition rate of Subject1 as training set (%)

| Algorithm                | Subject2 | Subject3 | Subject4 | Subject5 |
|-------------------------|----------|----------|----------|----------|
| Original image          | 89.89    | 36.12    | 5.01     | 2.84     |
| Logarithmic transformation | 94.12    | 78.12    | 10.02    | 7.20     |
| Gamma transform         | 91.20    | 36.88    | 13.03    | 12.02    |
| Histogram equalization  | 98.87    | 70.67    | 18.12    | 29.11    |
| MSR                     | 97.89    | 80.97    | 47.31    | 63.78    |
| DMQI                    | 97.01    | 99.10    | 95.05    | 95.97    |

Table 2 Recognition rate of Subject5 as training set (%)

| Algorithm                | Subject1 | Subject2 | Subject3 | Subject4 |
|-------------------------|----------|----------|----------|----------|
| Original image          | 5.01     | 11.02    | 31.78    | 57.21    |
| Logarithmic transformation | 6.34    | 15.78    | 35.21    | 72.78    |
| Gamma transform         | 7.02     | 13.11    | 36.09    | 72.99    |
| Histogram equalization  | 26.23    | 38.33    | 41.52    | 89.78    |
| MSR                     | 70.10    | 63.21    | 52.87    | 84.99    |
| DMQI                    | 48.70    | 54.55    | 68.24    | 94.78    |

From Table 1 in Table 2, it can be seen that the recognition rates of the traditional image enhancement algorithm and the illumination invariant feature extraction algorithm based on the Lambertian model are higher than the original image, which indicates that it is necessary to remove the illumination factor by preprocessing before feature extraction and classification recognition. In the image enhancement algorithm, the recognition effect of histogram equalization is better than the logarithmic transformation and gamma correction algorithm, but the recognition rate is still low. The recognition rate of the traditional image enhancement algorithm is much lower than that of the illumination invariant feature extraction algorithm based on the Lambert model. Both multi-scale retinal model (MSR) and dynamic morphological quotient image (DMQI) have achieved good recognition results, and dynamic morphological quotient image (DMQI) can better extract illumination invariant features and contain face details as much as possible.

5. Conclusion

In this paper, various methods of preprocessing were carried out on pictures under various illumination conditions, and the method proposed was verified by comparison experiments. Through experiments, it can be seen that the recognition accuracy of pre-processed picture was higher than that of the original one. The recognition accuracy was also very different after the pictures were preprocessed by different methods. Although the dynamic morphology quotient image (DMQI) can greatly improve the recognition accuracy of the picture, there is also a long way to go to develop the illumination preprocessing algorithm.
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