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Face Illumination Processing Using Wavelet Transform and Gradientfaces

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Abstract. In view of the problem of illumination, a new approach based on wavelet transform and gradientfaces for illumination processing is presented. Firstly, the method calculates wavelet transform and multilevel wavelet decomposition in logarithm domain. The low frequency coefficient is discarded partially. After reconstructed, the high frequency component of the face image is enhanced using gradientfaces. Secondly, the face invariant feature is extracted by Principal Component Analysis (PCA), the nearest neighborhood classifier using cosine distance is adopted for face classification. The experiment result on Yale B frontal face database demonstrates that the presented algorithm could recognize all of the test samples and the face recognition rate is 100%. Thus, this technique can overcome the effect of different degree of illumination efficiently.

Introduction

Currently, face recognition has become a hot topic in the research fields such as pattern recognition, image processing, machine vision, neural networks and cognitive science [1, 2]. FERET test showed that the changing of illumination and pose is the major challenge of current face recognition system [3]. The algorithms of processing light are mainly divided into three categories [4]: extracting illumination invariant feature, modelling the illumination changes and normalization the lighting conditions. The thought of extracting the illumination invariant feature is to extract illumination invariant feature component which is insensitive to light in the face image for face recognition [5]. The main idea of modelling the illumination changes is to explore the changing extent of the light conditions within the face image in some appropriate subspace or manifold of image space, then the model parameters of the characteristics of the face image are estimated by utilizing the methods such as self-quotient image method [6], light cone method [7] and the method based on spherical harmonic fundamental image [8], .etc. This kind of method needs to build a complete set of face images. However, building a complete set of face images is so complex in practice that the practical application of the above methods subjects to certain restrictions. The main idea of normalization the lighting conditions is that light was normalized to a standard form by image conversion or synthetic before human face recognition. Those methods are histogram equalization, gamma correction, logarithmic transformation, SFS (Shape Form Shading) [9] and 3D morphing technology [10]. etc. This transformation can achieve the purpose of the illumination elimination to reduce the impact of light, and then to recognize the normalized face.

A new face illumination processing algorithm is proposed in this paper. Wavelet transform is applied to face image in logarithmic domain, part of low-frequency coefficients are discarded. Using gradientfaces enhance the high-frequency details of the image after image reconstruction. Light processing effect is represented by recognition rate. Face illumination process flow diagram is shown in Fig. 1.

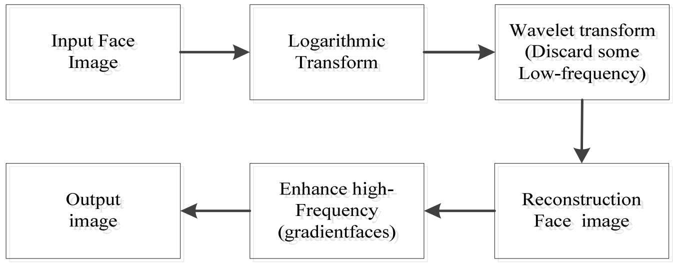


Figure 1. Face illumination process flow diagram.

Algorithm

The Wavelet Transform of the Image

If $L^2(R)$ has a multi-resolution analysis (MRA) $\{V_j\}_{j\in Z}$ and the corresponding scaling function $\varphi(x)$, a two-dimensional scale space $V_j^2 = V_j \otimes V_j$ of scales j is defined, where the symbol $\otimes$ represents space multiplied. Since the orthonormal basis of V_j is $\varphi_{j,n}(x) = 2^{-j/2}\varphi(2^{-j}x-n)$, the orthonormal basis $\{\varphi_{j,n}(x)\varphi_{j,m}(x)\}_{n,m\in Z}$ in V_j^2 has been obtained. The W_{j+1}^2 is used for denoteing the orthogonal complement of V_{j+1}^2 in V_j^2 .The $\psi(x)$ is used for denoting the corresponding one-dimensional wavelet with $\varphi(x)$. So three wavelet functions $\Psi^1 = \varphi\otimes\psi = \varphi(x)\psi(y)$, $\Psi^2 = \psi\otimes\varphi = \psi(x)\varphi(y)$ and $\Psi^3 = \psi\otimes\psi = \psi(x)\psi(y)$ in $L^2(R^2)$ can be obtained, which makes $\{\Psi^i(2^j x-k, 2^j y-l)\}$, where $j,k,l\in Z, i=1,2,3$ constitute the orthonormal basis. In the two-dimensional multi-resolution analysis, for the square integral two-dimensional image signal $f(m,n)\in L^2(R^2)$, assumes that $C_{0,mn} = f(m,n)$, the wavelet decomposition recurrence formula of two-dimensional image can be expressed as follows.

$$C_{j,mn} = \sum_{k,l} C_{j-1,kl} h_{k-2m} h_{l-2n} . \tag{1}$$

$$D_{j,mn}^1 = \sum_{k,l} C_{j-1,kl} h_{k-2m} g_{l-2n} . \tag{2}$$

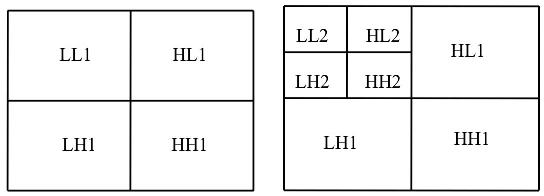
$$D_{j,mn}^2 = \sum_{k,l} C_{j-1,kl} g_{k-2m} h_{l-2n} . \tag{3}$$

$$D_{j,mn}^3 = \sum_{k,l} C_{j-1,kl} g_{k-2m} g_{l-2n} . \tag{4}$$

Where $h(n) = <\varphi, \varphi_{-1,n}>$, $g(n) = <\psi, \varphi_{-1,n}>$, and has:

$$g(n) = (-1)^n h(1-n). \tag{5}$$

Two-dimensional wavelet decomposition of image can be represented graphically in Figure 2. As shown in Fig. 2 (a), the image is transformed into four sub-images after wavelet decomposition level 1. LL1 is low-frequency components. HL1, LH1 and HH1 are respectively horizontal detail component, vertical detail component and diagonal detail component, which are half the size of the original image. If the need for image wavelet decomposition level 2 is as shown in Fig. 2 (b), the component LL1 is further broken down into a low frequency component LL2 and three detail components HL2, LH2 and HH2, and the size is half of the LL1. If the next level of image decomposition is needed, then repeat the above steps for LL2 decomposition, and so on. Finally, the sub-image LLn which obtained after n-level wavelet decomposition of the original image is low-frequency approximation.



(a)one level decompose (b)two level

Figure 2. The Wavelet decomposition of the image.

Gradientfaces

Gradientfaces [11] is defined as follows:

For any direction gray image $I(x,y)$, x direction neighborhood point of pixel point (x,y) is $(x+\Delta x, y)$, then:

$$I(x+\Delta x, y) = R(x+\Delta x, y)L(x+\Delta x, y). \tag{6}$$

Eq. (8) subtracts eq. (1) to get:

$$I(x+\Delta x, y) - I(x,y) = R(x+\Delta x, y)L(x+\Delta x, y) - R(x,y)L(x,y). \tag{7}$$

L is approximate smooth and slow to change, then:

$$\begin{aligned} I(x+\Delta x, y) - I(x,y) &\approx R(x+\Delta x, y)L(x+\Delta x, y) - R(x,y)L(x,y) \cdot \\ &\approx [R(x+\Delta x) - R(x,y)]L(x,y) \end{aligned} \tag{8}$$

When Δx tends to 0, then:

$$\frac{\partial I(x,y)}{\partial x} \approx L(x,y)\frac{\partial R(x,y)}{\partial x} \cdot \tag{9}$$

Similarly, in the direction of y :

$$\frac{\partial I(x,y)}{\partial y} \approx L(x,y)\frac{\partial R(x,y)}{\partial y} \cdot \tag{10}$$

Eq. (12) is divided by eq. (11), then:

$$\frac{\frac{\partial I(x,y)}{\partial y}}{\frac{\partial I(x,y)}{\partial x}} \approx \frac{\frac{\partial R(x,y)}{\partial y}}{\frac{\partial R(x,y)}{\partial x}} \cdot \tag{11}$$

Gradientfaces is defined as follows:

$$G = \arctan(Iy/Ix) \cdot \tag{12}$$

Where $Iy = \partial I(x,y)/\partial y$ and $Ix = \partial I(x,y)/\partial x$ are respectively the image gradient in the direction of y and x, and $G \in [-\pi, \pi]$. In practice, in order to calculate the gradientfaces, first need to calculate the gradient of face image in the direction of x and y. In order to successfully calculate gradient values, need to use Gaussian kernel to smooth face image, namely, the gradient in the direction of x and y are calculated after the convolution of face image and Gaussian kernel.Expression of Gaussian kernel function is shown as follows:

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right). \tag{13}$$

Among them, σ is a standard difference of Gaussian kernel.

Experiments

Face Database

Our experiment is conducted on the Yale database B, which contains images of ten individuals with nine pose and 64 illuminations per pose. The frontal face images of all subjects, each with 64 different illuminations are used for evaluation. All images are cropped and resized to 128×128. They are divided into five subsets based on the angle of the lighting source direction. The five subsets are: subset 1 (0°-12°), subset 2 (13°-25°), subset 3(26°-50°), subset 4 (51°-77°), subset 5(above 78°). There are total 640 images: 70,120,120,140,190 from subset 1 to subset 5, respectively.

Experimental Results

PCA method (feature vector number d is 50) is used to extract feature in this paper, and the nearest neighbor classifier based cosine distance is used to classification determination. After light treatment, mean and variance of face images is respectively normalized to 0 and 1.

Table 1. Experiments of face recognition(Yale B face database).

The type of wavelet Decomposition (level)	σ of the formula	The type of wavelet Decomposition (level)	σ of the formula
db2(2)	0.1-1.1	sym2(2)	0.1-1.1
db3(2)	0.8-1.6	sym3(2)	0.5-0.9
db6(2)	0.2-1.7	sym4(2)	0.5-1.6
db8(2)	0.9-1.5	sym8(2)	0.1-0.4
db10(2)	0.1-1.7	coif2(2)	0.7-1.5
db12(2)	0.6-1.5	coif4(2)	0.1-1.5
db16(2)	0.6-1.8	bior3.3(2)	0.1-1.5
db18(2)	0.5-1.5	bior5.5(2)	0.8-1.8
db19(2)	0.1-1.2	rbio3.3(2)	0.1-1.3
db20(2)	0.8-1.0	rbio5.5(2)	0.9-1.4

To find the best type of wavelet, wavelet decomposition level and deviation range of the Gaussian kernel standard value σ of the formula (13) in experiment, the type of wavelet, wavelet decomposition level and the value of σ are tested in this paper. The parameters are selected through experiments. When correct recognition rate in Yale B face database was 100%, the parameter values are as shown in Table 1.

As can be seen from Table 1, different types of wavelets such as db2, db3, db6, sym2, sym3, coif2, bior3.3, rbio3.3 are studied experimentally. The type of wavelet, wavelet decomposition level and the value of σ are selected appropriately. So the illumination of face image is efficiently processed. As shown in Table 1, the face recognition rate is 100% when the wavelet is db2 with level 2 and the value range of σ is in 0.1-1.1.

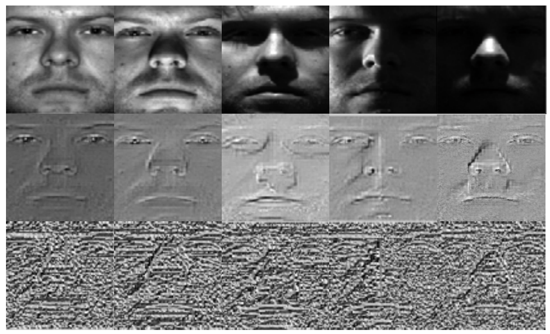


Figure 3. Face image processed with different methods.

The effect comparisons that the same person in different subsets of the face image after the light treatment are as shown in Fig. 3. The first line the original image, the second line displays the face images by wavelet transform processing, and the third line shows the face image after the processing of the proposed method. As we can see from the figure, the face image after the light treatment by used proposed method can display its general outline and retain important facial feature.

Comparison of Experiment Results

Table 2 shows the face recognition error rate comparison of several different ways after the light treatment at Yale B face database. As we can see from Table 2, the average false recognition rate of face with directly gradientfaces algorithm [11] is 0.15%, the average false recognition rate of face with directly discrete cosine transform (DCT) [12] is 0.55%, the average false recognition rate of face with directly OLHE [13] is 0.90%, while the average false recognition rate of the use of the proposed method of treatment is zero. Comparison results can be seen from Table 2, the recognition effect of the proposed light treatment method is superior to several other light treatment methods.

Table 2. Comparison of experiment results.

Methods	The rate of face recognition(%)				
	subset2	subset3	subset4	subset5	average
gradientfaces	0	0	0.71	0	0.15
DCT	0	0	0.18	1.71	0.55
OLHE	0	0	2.60	1	0.90
Our method	0	0	0	0	0

Conclusion

A face light processing algorithm based on wavelet transform and gradientfaces is proposed in this paper. Firstly, wavelet transform is used to the facial image in the logarithmic domain. The image is multi-level wavelet decomposed. Parts of low-frequency coefficients are discarded.

Gradientfaces is processed after reconstructed image. Next, facial feature in the face image is extracted by the principal component analysis. Finally, face image is recognized using the neighbor classifier based on cosine distance. Experimental results in the Yale B face database show that the appropriate selection of the type of wavelet, wavelet decomposition level and the value of the Gaussian kernel function σ, face recognition rate can reach 100% after face illumination processing, which can weaken the effect of non-uniform illumination to the face image.

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