LOCAL QUATERNIONIC GABOR BINARY PATTERNS FOR COLOR FACE RECOGNITION

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ABSTRACT

In this paper, a novel color face recognition method is proposed based on Local Binary Patterns (LBP) of Quaternionic Gabor features (QGF). By introducing Quaternion Gabor analysis into image representation, we make full use of the interrelationship among different color channels to enhance the performance of the face recognition system. Moreover, the QGF are used to encode the positions and attributes of the face elements. Non-parametric transformation is then imposed on these QGF using LBP method to obtain the robustness against variations of pose, illumination and facial expressions. Compared with the monochromatic face recognition systems, which nowadays dominate the marketplace and research field, this approach materializes the strong potential use of color face recognition system by establishing invariant quaternion wavelet features of color images. The experimental results on the open face database testify the validity of the proposed method under severe noise corruption and distinct variations of scale, illumination and facial expressions.

***Index Terms*—** Quaternionic Gabor Feature, Local Binary Pattern, Color Face Recognition

1. INTRODUCTION

Face recognition is one of the most appealing topics in computer vision research due to technical and commercial demands. Various algorithms are advanced to find a rational solution, such as PCA, LDA, SVM, Kernel Methods, Neural Networks and to name a few [1]. Recently, Gabor-based methods have been proved as a promising way towards achieving high accuracy face recognition [2][3][4]. As for this kind of method, B. Zhang's work [5] published in 2007 even achieved the best performance in terms of recognition rate when compared with other well-known recognition systems, such as Eigenface [6] and GFC [3]. This approach introduced Local Binary Pattern (LBP) histogram [7] into Gabor based features and achieved good resistance to variant facial expression, lighting, and aging of subjects, which are the main error sources for the recognition systems. In essence, the competitive advantage lies in its mechanism that Gabor kernels capture the structure information of face images while LBP histogram encodes the relationship of these structures.

The abovementioned recognition methods are all used in the monochromatic face recognition systems. Nowadays these systems are still leading the development of state-of-the-art technologies. Meanwhile, the cost of chromatic image computing undergoes a sharp decrease with the emergence of high-speed signal processors. The potential use of color image recognition systems becomes more and more attractive. The popular means to deal with the color information is to consider the different color planes as independent channels and the straight concatenation operations are imposed to obtain the final results [8][9]. However, the interrelationship of multiple color planes is ignored in such manner. In Jones's work [10], the color pixels are processed as units in the quaternion vector space and it has been proved that the integral use of different color planes can greatly increase recognition accuracy. Motivated by Jones's pioneer work on quaternion wavelet representation of color features and the observation that better performance could be induced by combination of non-parametric histogram with Gabor features, we introduce LBP method into quaternion Gabor analysis to establish features invariant to changes in scale, illumination and facial expressions. Rather than EBGM method employed by Jones, which needs to manually label face features and organize these features into an attributed relational graph using Quaternion Gabor analysis, we highlight our color face recognition system with better automaticity and higher recognition rate.

This paper is organized as follows. Section II describes our color face recognition method, which is based on the Local Quaternionic Gabor Binary Patterns (LQGBP). This is followed by the performance evaluation of the proposed prototype system in Section III, where comparison with other well-known face recognition system is presented on some open face databases. Finally, conclusion remark is drawn in Section IV.

2. COLOR FACE RECOGNITION BASED ON LQGBP

There are many variants for the definition of Quaternionic Gabor Wavelets (QGW). It is formulated in Jones's work as,

$$F_h(\vec{x}) = \mu \frac{\|\overrightarrow{k_h}\|^2}{\sigma^2} e^{-\frac{\|\overrightarrow{k_h}\|^2 \|\vec{x}\|^2}{2\sigma^2}\left(\cos\overrightarrow{k_h}.\vec{x} - e^{-\frac{\sigma^2}{2}}\right)} \quad (1)$$

where $\vec{x}$ is the 2D spatial location vector, $\overrightarrow{k_h}$ indicates the direction of the sinusoidal oscillation of the filter and μ is a unit pure quaternion which represents a specific direction in RGB color space. To extract multi-scale and multi-oriented QGF, we define a QGW set with constant octave band,

$$F_{u,v}(x,y) = \mu \frac{f_m^2}{2^u \sigma^2} e^{-\frac{f_m^2}{2^{u+1}\sigma^2}(x^2+y^2)} \left\{ e^{\frac{f_m}{2^{0.5u}}\left[x\cos\frac{v}{8} + y\sin\frac{v}{8}\right]} - e^{-\frac{\sigma^2}{2}} \right\} \quad (2)$$

where $\sigma = 15$ and $f_m = 0.2$, these two parameters respectively denote the standard deviation of the Gaussian envelope and the center frequency at the smallest scale. Here we select $u = 0,1,\ldots,4$ and $v = 0,1,\cdots,7$ to uniformly partition the scale and the orientation scope, whereby it results in image decomposition at 5 scales and 8 orientations. Because of the substantial power in natural signals at low frequencies, this DC sensitivity is eliminated by the term in the brace bracket to avoid a positive bias of the response. In order to find an adaptive selection of μ and thus realize homogeneous projection in the color vector space, the computation of μ in our face recognition system is summarized as follows:

Step1. Provide a simplified version of the covariance matrix $\mathbf{S}$ for the three color planes in the original image,

$$\mathbf{S} = \frac{1}{\mathrm{M}} \sum_{\mathrm{M}} \begin{bmatrix} \mathbf{p_r} \\ \mathbf{p_g} \\ \mathbf{p_b} \end{bmatrix} \begin{bmatrix} \mathbf{p_r} \\ \mathbf{p_g} \\ \mathbf{p_b} \end{bmatrix}^{\mathrm{T}} - \overline{\mathbf{p_r}}^2 - \overline{\mathbf{p_g}}^2 - \overline{\mathbf{p_b}}^2 \quad (3)$$

where M is the number of color pixels; $\mathbf{p_r}$, $\mathbf{p_g}$ and $\mathbf{p_b}$ are respectively the normalized pixel value matrix of each RGB channel, which satisfy the constraint $\overline{\mathbf{p_r}} \approx \overline{\mathbf{p_g}} \approx \overline{\mathbf{p_b}}$, where operator outputs the mean value of the given matrix $\overline{[\cdot]}$.

Step 2. Impose PCA analysis on the covariance matrix $\mathbf{S}$ and determine the pure quaternion μ as the principal eigenvector of $\mathbf{S}$ (further normalized by $-1/\sqrt{3}$).

Once the color axis μ is determined, QGF is extracted by the convolution of the original color image $\mathrm{I}^{\mathrm{q}}(\mathrm{x},\mathrm{y})$ and the given Quaternionic Gabor kernel $\mathrm{F}_{\mathrm{u,v}}(\mathrm{x},\mathrm{y})$. No matter what transformation happens in the RGB vector space between two corresponding color face images, we always depict the convolution output $\mathrm{O}^{\mathrm{q}}(\mathrm{x},\mathrm{y})$ as two parts, i.e. $\mathrm{O}^{\mathrm{q}}_{\parallel\mu}(\mathrm{x},\mathrm{y})$ and $\mathrm{O}^{\mathrm{q}}_{\perp\mu}(\mathrm{x},\mathrm{y})$, where the former one is parallel to the principal color component μ of the original image while the latter one is the compensatory one and orthogonal to μ. By adopting QGW analysis, we can represent two face images by projecting them according to the principal eigenvector to achieve the homogeneous results. Moreover, the QGW transform processes the three color planes integrally to capture the multiscale and multi-oriented color features.

Two kinds of QGF are defined in our face recognition system. Firstly, the convolution result can be written as

$$O^q(x,y) = I^q(x,y) \otimes F_{u,v}(x,y) = a + bi + cj + dk \quad (4)$$

where the real part can be approximated by the parallel part $\mathrm{O}^{\mathrm{q}}_{\parallel\mu}(x,y)$ and the imaginary parts consist of the orthogonal one, namely $\mathrm{O}^{\mathrm{q}}_{\perp\mu}(x,y)$. Then a magnitude color image is established from the three imaginary parts, i.e. one-to-one mapping from coefficients b, c, d to R, G, B channels. Another color image is also set up from the arguments between the imaginary parts and the real part, that is

$$\varphi_1 = \mathrm{arctan2}(b/a) \quad (5)$$

$$\varphi_2 = \mathrm{arctan2}(c/a) \quad (6)$$

$$\varphi_3 = \mathrm{arctan2}(d/a) \quad (7)$$

One example of QGF is illustrated in Fig. 1. There are 8 orientations along each row and 5 scales along each column for two kinds of QGF images.

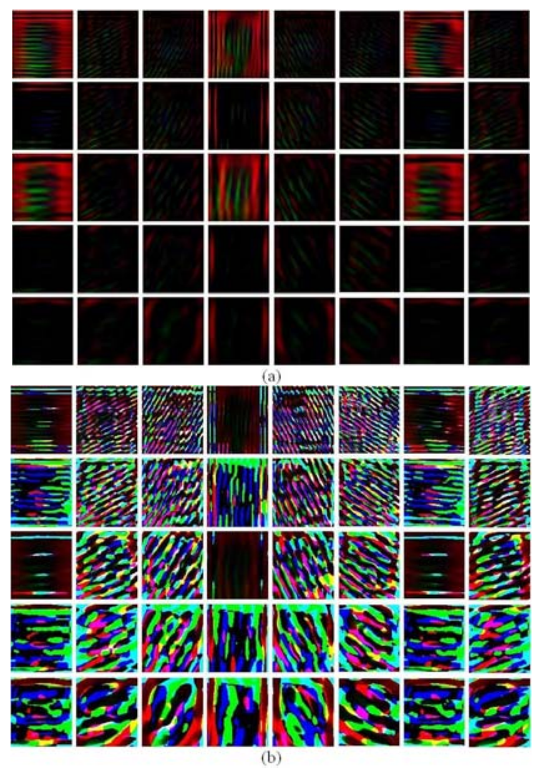

Fig. 1 QGF images: (a) magnitude (b) argument

It can be deduced that magnitude value is very sensitive to the variations of illumination. As for arguments, they are robust to the illumination contrast variations while show instability under pose and expression changes. It has been proved that non-parametric histogram method could enhance the robustness against variations in pose, illumination and expressions for local feature-based approach. Non-parametric approaches take no assumption on the underlying data density. Instead, they encode the relationship between the local features and the resultant descriptor for face recognition is near invariant under varied imaging conditions. LBP histogram method is one type of the non-parametric approaches and is widely exploited in face recognition tasks to achieve the aforementioned merits [7][11].

In this section, we incorporate LBP histogram method to establish local invariant descriptors for QGFs, which are named LQGBP descriptor. We unfold the construction procedure of LQGBP descriptors as follows:

Step 1. Generate eighty feature images through QGF at 5 scales and 8 orientations, as shown in Fig. 1.

Step 2. Each QGF image $f(\mathbf{c})$ is further mapped to $f'(\mathbf{c})$ and $f'(\mathbf{c})$ is obtained by the following rule,

$$\mathrm{A}(\mathbf{c_i}) = \begin{cases} 1 & \text{if } f(\mathbf{c_i}) \geq f(\mathbf{c}) \text{ and } \mathbf{c_i} \subset \mathbf{\Omega_c} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

$$f'(\mathbf{c}) = \sum \mathrm{A}(\mathbf{c_i}) \times 2^{i} \tag{9}$$

where $\mathbf{c}$ indicates the position, "$\mathbf{\Omega}$" denotes a neighborhood system.

Step 3. The output QGF images after local binary mapping are divided into 8×8 subregions and represented by the stacks of the local histograms of these subregions. These local histograms contribute to a global invariant descriptor of the QGF images. For two corresponding magnitude /argument QGF images, the similarity measure is defined as follows:

$$S = \sum_{s,o,c} (H_1 \cap H_2)/N \tag{10}$$

$$N = 6N_p \times N_s \times N_o \tag{11}$$

where the subscript of H is used to indicate the local histogram from different face images; symbols s, o, c further point out at which scale, orientation and position histogram H is computed; N_p is the number of the total pixels in the original image; N_s and N_o respectively compute the number of scales and orientations; the notation "$\cap$" retains the smaller individual of the two matrices.

The flowchart shown in Fig. 2 delineates the proposed face recognition method.

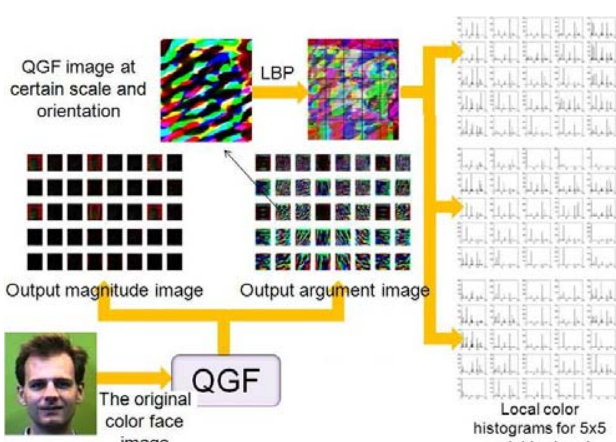

Fig. 2 The configuration of LQGBP-based color face recognition system

3. EXPERIMENTAL RESULTS

In the color face recognition tests, we find the trade-off between computational complexity and recognition rate when the number of histogram bins is set to 16 and subregion size is bounded by an 8×8 rectangle window. The local binary mapping is performed within a 3×3 neighborhood system. The adopted database is selected from Essex, i.e. Essex 94, Essex Grimace and Essex 96. Essex database is available at:

http://cswww.essex.ac.uk/mv/allfaces/index.html.

In Essex 94, the image resolution is 180×200 pixels (portrait format).The subjects sit at a fixed distance from the camera and are required to speak whilst one image sequence is acquired. The speech is enforced to introduce facial expression variations. In Essex Grimace, the image resolution is also 180×200 pixels. A 20-frame length image sequence was captured for each individual using a fixed-distance camera, in which the subject moves his/her head and makes grimaces. The procedure to obtain Essex 96 is quite similar to that of Essex 94 except that there are distinct scale variations between the samples, and the image resolution is 196×196 pixels.

Some terms are needed to evaluate the accuracy of a biometric system. Here we introduce the concept of Rank-1 verification accuracy and the Equal Error Rate (EER). The former one counts for the rate that the right individual in the gallery set happens to rank the first. Since it is beneficial to consider the false-acceptance rate and false-rejection rate together, we also introduce the EER to measure the identification accuracy of our face recognition system. This is the rate at which the false-acceptance rate and false-rejection rate take the same value. The false-acceptance rate scores when the system incorrectly accepts an impostor while the false-rejection rate states the percentage of instances an authorized user is falsely rejected.

Database Essex 94 is applied to Expt. I, II, and III. In Expt. I, two samples are gathered for each individual. One composes the gallery and the other is used as the probe. It is used to estimate the recognition rate in absence of external factors such as lighting, noise, variations of expression and scaling. In Expt. II, only one sample is selected for each individual. Then, each sample is further distorted and generates the probe set assuming a linear light source with 40% transparency is adopted. It is used to obtain the performance evaluation under illumination variations. Taking the same gallery set as in Expt. II, we again corrupt the samples in Expt. III to form the new probe set by imposing zero mean and 1% variance Gaussian noise. This experiment is used to evaluate the robustness of our recognition system to noise. The database for Expt. IV is Essex Grimace. Similar to Expt. I, two samples are acquired for each individual. One is used for the gallery and the other acts as the probe. This experiment is designed to testify the resistance to severe expression variations. Finally, we select two samples per face from database Essex 96 in Expt. V to measure the robustness against scaling variations.

Samples in the probe and gallery set of each experiment are given in Fig. 3. The corresponding verification and identification accuracy of three methods are listed in Table 1, including Jones's method, LGBP method and our method. LGBP can represent the basic mechanism of Zhang's method [12] except for some extra post-processing steps, which can also be added to our scheme. Here we just compare LGBP method with ours to see the improvement induced by quaternion Gabor based color analysis. It is observed that our method has comparable performance to other two methods under noises and variations of expression, and much higher tolerance in lighting variations. The main reason is that non-parametric transform of QGF could not only capture much about hue information but also the relationship between image structures, which are both insensitive to illumination variations. However, it is a bit weaker when dealing with distinct scaling variations in Expt. V. The main reason might be that the color inconsistence between two scenes of different scales introduce errors into homogeneous projection in the color vector space.

(a)(b)(c)(d)
(e)(f)(g)(h)

Fig. 3 Samples in (a) gallery set of Experiment I, II, and III; (b), (c), and (d) probe sets of Experiment I, II, and III; (e) ,and (f) gallery and probe set of Experiment IV; (g) and (h) gallery and probe set of Experiment V.

	DB size	Description	LGBP	Jones's (DB 132)	LQGBP
Expt. I	50 (99)	Rank-1	96%	63.3%	94% (96%)
		EER	4.1%	12.3%	4.2% (2.2%)
Expt. II	50	Rank-1	76%	-	98%
		EER	20.6%	-	5.7%
Expt. III	50	Rank-1	100%	-	96%
		EER	0%	-	7.1%
Expt. IV	18	Rank-1	94.4%	-	100%
		EER	1.0%	-	4.3%
Expt. V	50	Rank-1	82%	-	82%
		EER	11.0%	-	20.3%

Table. 1 comparison on LGBP, Jones's method, and LQGBP

4. CONCLUSIONS

In this paper, we propose a color face recognition method based on the Local Quaternionic Gabor Binary Patterns (LQGBP) descriptor. It makes full use the interrelationship among different color channels and achieves promising performance under noises and variations of lighting, and expressions. In the future work, we will focus on enhancing our recognition system under partial occlusion and variations of scaling and aging.

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