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LPQ and LBP based Gabor filter for face representation

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ABSTRACT

Sometimes realistic face representation is confronted with blur or low-resolution face images, as a result, existing classification methods are not powerful and robust enough. This paper proposes a novel face representation approach (GLL) which fuses Gabor filter, Local Binary Pattern (LBP) and Local Phase Quantization (LPQ). In the process of Gabor filter, it uses Gabor wavelet functions with two scales and eight orientations to capture the salient visual properties in face image. On this basis of Gabor features, we acquire LBP features and LPQ features, respectively, so as to fully explore the blur invariant property and the information in the spatial domain and among different scales and orientations. Experiments on both CMU-PIE and Yale B demonstrate the effectiveness of our GLL when dealing with different condition face data sets.

1. Introduction

Face recognition plays an important role in many applications, such as human computer interface, visual surveillance, access control, law enforcement, and more generally image representation [1]. With the complexity and nonrigidity of face, face representation has become a verification benchmark for various pattern recognition algorithms [2].

Various algorithms have been developed and tested for face representation. Among them, dynamic texture-based approach [3] is proposed to the recognition of facial action units. The recently proposed local binary pattern (LBP) operator [4] has been successfully applied to facial expression [5] and face recognition [6]. Local phase quantization (LPQ) is a novel method which is used for recognition of blurred faces [7], LPQ is based on quantizing the Fourier transform phase in local neighborhoods, in face image analysis, histograms of LPQ labels computed within local regions are used as a face descriptor similarly to the widely used LBP methodology for face image description. In [8], Marsico et al. provide FAce Recognition against Occlusions and Expression Variations (FARO) as a new method based on partitioned iterated function systems (PIFSs), which is quite robust with respect to expression changes and partial occlusions. Recently, the fusion method combined Gabor filter has been key focus to many researchers [9–11]. Gabor wavelets capture the local structure corresponding to specific spatial frequency, spatial locality, and selective orientation which are demonstrated to be discriminative and robust to illumination and expression changes. Lei et al. provide a face representation and recognition approach by combined the Gabor filters with multiscale and multiorientation to local binary pattern analysis [12].

In this paper, we propose a novel face representation method which explores not only the blur invariant property, but also the information in the spatial domain and among different scales and orientations. First, the multiscale and multiorientation representations are derived by convolving the face image with a Gabor filter bank and formulated as serial transformed images. Second, the LPQ labels [13] computed within local regions are used as a face descriptor for face transformed image description. Third, LBP operator is applied on the face transformed image of Gabor filter. In this way, we encode the neighboring information and the texture information not only in image space but also among different scales and orientations of Gabor faces. Finally, the final feature vectors are acquired from the fusion transformed images by concatenated histograms.

We introduce the basic approach of face representation in Section 2, containing Gabor filter, LBP and LPQ. Then Section 3 describes the experimental results and Section 4 finally presents the concluding remarks.

2. Face representation

2.1. Gabor wavelets

Gabor kernels are similar to the receptive field profiles in cortical simple cells, which are characterized as localized,

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orientation selective, and frequency selective. A family of Gabor kernel is the product of a Gaussian envelope and a plane wave:

$$\psi_k(z) = \frac{k^2}{\sigma^2}\exp\left(-\frac{k^2}{2\sigma^2}z^2\right)\left(\exp(ikz) - \exp\left(-\frac{\sigma^2}{2}\right)\right) \quad .(1)$$

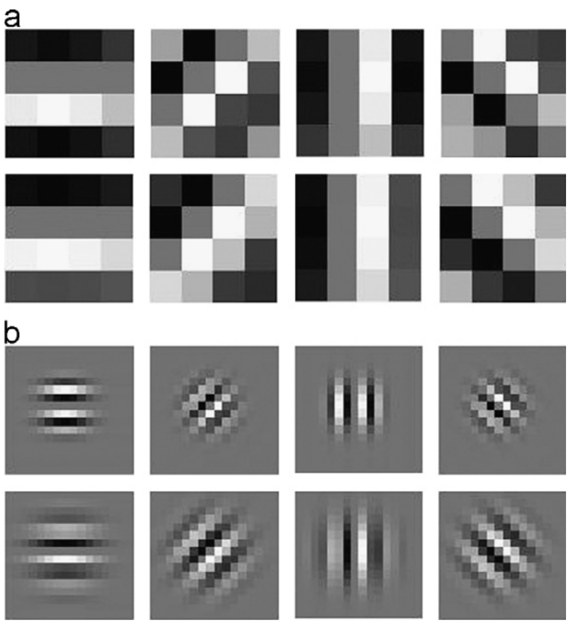

Fig. 1. Gabor filters of two different scales and four different orientations: (a) size of window: 4×4 and (b) size of window: 16×16.

where $z=(x,y)$ is the variable in spatial domain and k is the frequency vector, which determines the orientations (μ) and the scales (v) of Gabor kernels. In this paper, μ and v are orientation factor and scale factor respectively. Different selection of subscript μ and v gives different Gabor kernel [12]. We choose $\mu=0,1,2,3$ and $v=0,1$, thus totally we have eight Gabor functions to be used. The real part of the Gabor kernels used in our experiments is shown in Fig. 1.

Given an image $I(x,y)$, its Gabor transformation at a particular position can be computed by a convolution with the Gabor kernels:

$$G_k(x,y) = I(x,y) * \psi_k(x,y). \quad (2)$$

2.2. Local binary patterns

LBP was first introduced by Ojala et al. in [14]. It is a powerful method of texture description based on statistical analysis and shows its practical use in texture description. Although many variants of LBP are widely used for face analysis due to their satisfactory classification performance, they have not yet been proven compact. So feature fusion is considered to be an effective approach. LBP using the maximization of mutual information shows a better performance in face analysis [15]. The operator labels the pixels of an image by thresholding the 3×3 neighborhood of each pixel with the center pixel and considering the result as a binary number. The LBP result can be expressed as follows:

$$LBP_{P,R}(x_c, y_c) = \sum_{n=0}^{7} \delta(g_n - g_c) 2^n. \quad (3)$$

where g_c is a center pixel value positioned at (x_c,y_c), g_n is one of the eight surrounding center pixel values with the radius R, P is

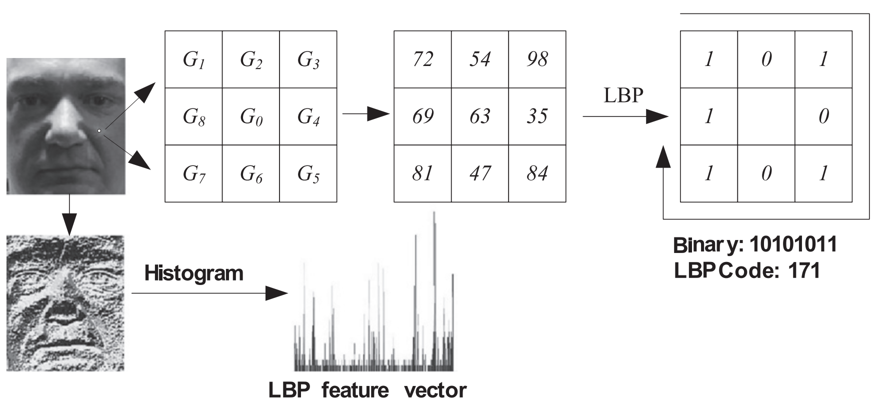

Fig. 2. LBP operator algorithm.

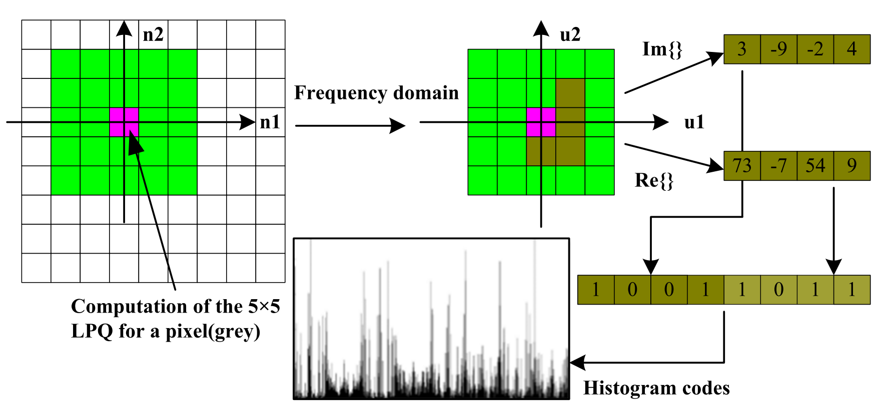

Fig. 3. A simplified procedure for computing LPQ.

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the whole neighborhood number, and a sign function $\delta(\cdot)$ is defined such that

$$\delta(x)=\begin{cases}1 & \text{if } x>0,\\ 0 & \text{otherwise.}\end{cases} \tag{4}$$

The histogram of the LBP labels can be used as a texture descriptor. See Fig. 2, for an illustration of the basic LBP operator.

The original LBP with P neighborhoods has 2^P different binary patterns. However, Ojala et al. [16] observed that the natural images generally contain a small number of LBP codes, which are called the uniform LBP. Uniform LBP contains a maximum of two bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular. These uniform patterns represent the majority of texture microstructures.

2.3. Local phase quantization

Ojansivu et al. [13] proposed a spatial blurring method. The spatial blurring is represented by a convolution between the image intensity and a point spread function (PSF). Assuming that an original image is $f(x)$, and an observed image is $g(x)$, then, the discrete model for spatially invariant blurring of $f(x)$ can be expressed by a convolution:

$$g(x)=f(x)\otimes h(x). \tag{5}$$

where $h(x)$ is the PSF of the blur, $\otimes$denotes 2-D convolution and x is a vector of coordinates $[x,y]^T$. In the Fourier domain, this correspond to

$$G(u)=F(u)\otimes H(u). \tag{6}$$

where $G(u)$, $F(u)$ and $H(u)$ are the discrete Fourier transforms (DFT) of the blurred image $g(x)$, the original image $f(x)$, and the PSF $h(x)$, respectively, and u is a vector of coordinates $[u,v]^T$. The magnitude and phase can be separated from:

$$|G(u)|=|F(u)|\cdot|H(u)|,\angle G(u)=\angle F(u)+\angle H(u). \tag{7}$$

The blur PSF $h(x)$ is centrally symmetric, namely $h(x)=h(-x)$, its Fourier transform is always real-valued, and as a consequence its phase is only a two-valued function, given by

$$\angle H(u)=\begin{cases}0 & \text{if } \; H(u)\geq 0,\\ \pi & \text{if } \; H(u)<0.\end{cases} \tag{8}$$

In LPQ, the phase is examined in local neighborhoods N_x at each pixel position x of the image $f(x)$. These local spectra are computed using a short term Fourier transform defined by

$$F(u,x)=\sum_{y\in N_x} f(x-y)e^{-j2\pi u^T y}. \tag{9}$$

where $x\in\{x_1,x_2,\cdots,x_N\}$ consist of simply 1-D convolution for the rows and columns successively. The local Fourier coefficients are computed at four frequency points $u_1=[a,0]^T$, $u_2=[0,a]^T$,$u_3=[a,a]^T$, and $u_4=[a,-a]^T$, where a is a sufficiently small scalar to satisfy $H(u_i)>0$. For each pixel position this results in a vector:

$$F(x)=[F(u_1,x),F(u_2,x),F(u_3,x),F(u_4,x)]. \tag{10}$$

Through observing the signs of the real and imaginary parts of each component in $F(x)$, the phase information can be counted using a simple scalar quantization:

$$q_i=\begin{cases}1 & \text{if } g_j\geq 0,\\ 0 & \text{otherwise.}\end{cases} \tag{11}$$

where g_j is the j-th component of the vector $G(x)=[\mathrm{Re}\{F(x)\}, \mathrm{Im}\{F(x)\}]$.

Then, the label image $f_{LPQ}(X)$ is represented as

$$f_{LPQ}\left(x\right)=\sum_{j=1}^{8} q_j(x)2^{j-1}. \tag{12}$$

In Fig. 3, an illustration of the computing LPQ representation scheme is given.

2.4. Face description and recognition

In this subsection, we describe our face representation system. First, we get the eight transform images of the original image using Gabor filter, then acquire the histogram codes of LBP and the histogram codes of LPQ (see Fig. 4), respectively.

Finally we use nearest-neighbor classification in the histogram distance for face recognition:

$$Eu(p,q)=\sqrt{\sum_k (p_k-q_k)^2}. \tag{13}$$

Fig. 4. Face description using LPQ.

Table 1
Recognition accuracy of PIE database.

Method	Correct recognition rate (%)
LBP	47.9
LPQ	57.7
Gabor+LBP	57.4
Gabor+ LPQ	61.3
Gabor +LBP+ LPQ	71.9

Fig. 5. Face images from the PIE database.

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Fig. 6. Examples of images from the Yale database.

Here p, q are image region descriptors (histogram vectors), respectively.

In the experiments below, face recognition employs the Euclidean distance nearest-neighbor classifier to find the image in the database with the best match.

3. Experimental results

With the following experimental results we validate the theoretical basis and demonstrate the accuracy of our devised image feature localization method.

3.1. Experimental comparisons on the CMU-PIE database

CMU-PIE facial image database is a publicly available and popular database for benchmarking face recognition methods. This database has 11,560 faces, comprising 68 classes with about 170 faces per class. The size of cropped image is 32×32 pixels for the PIE database, and the face images are formatted with 256 Gy levels per pixel (see Fig. 5).

For the experiment on the PIE database, we choose from the 1st to 30th frontal view faces to train the classifiers, and use faces from 101st to 120th as test images (which vary in illumination and pose), therefore, the train set contains 2040 face images, and the test set contains 1360 face images.

The tests are summarized in Table 1, where it can be seen that GLL has lower error rates than LPQ and LBP in all train tests. While Gabor+LPQ have error rates around 40%, the proposed GLL method has an error rate as low as close to 30%.

3.2. Experimental comparisons on the Yale B database

Faces in the Yale database have a large variation in terms of both expressions and illumination, as shown in Fig. 6. Tests on the Yale database can be considered as an evaluation of the robustness of the face recognition algorithms to variation in expression and illumination. For the Yale database, because the test image set should not overlap the training image set, we choose the training images from the 1st to 6th frontal view faces per subject, and use the 7th to 11th images (which vary in illumination and expression) as query test images. We then count the number of correct classifications.

Table 2 gives the experimental results on the Yale B face database. It is seen that the proposed GLL approach has the lowest error rate in comparison with LBP, LPQ, Gabor+LBP, and Gabor+LPQ.

Table 2
Recognition accuracy of YALE database.

Method	Correct recognition rate (%)
LBP	72
LPQ	81.3
Gabor+LBP	74.7
Gabor+ LPQ	88.0
Gabor +LBP+ LPQ	90.7

4. Conclusions

In this study, we proposed a method for accurate and efficient face representation method which makes a significant contribution to the problem of face recognition. The proposed method is based on multiresolution Gabor filter, LBP and LPQ, the fusion feature approach fully utilize the blur invariant property and the texture information. Experimental results clearly show that GLL illustrates a favorable performance on the CMU-PIE and Yale B database compared to related method. Experimental results show that this face representation works comparable to some existed methods. The main shortcoming of the method has higher computational complexity; therefore, the problem of adaptive feature selection of the face representation will be addressed in the future research.

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