

A Novel Approach for Face Recognition Using Fusion of Local Gabor Patterns

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ABSTRACT

For face recognition, Gabor features are effectively used. But, only a few approaches used Gabor phase features and they are performing worse than the Gabor magnitude features. To determine the potential of Gabor phase and its fusion with magnitude for face recognition, in this paper, we have proposed local Gabor XOR pattern (LGXP) operator, which encode Gabor phase. Then we introduce block-based Fisher's linear discriminant (BFLD) for reduce dimensionality of proposed operator and at same time discriminative power also get enhanced. At last, by using BFLD we fuse Gabor phase and Gabor magnitude for face recognition. We evaluate our method for FERET database. Also, we perform comparative experimental studies of different local patterns.

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1. INTRODUCTION

Face recognition is one of the most typical applications in image processing. Its used in many areas such as entertainment, information security and surveillance [11]. In last few decades, numerous approaches have been proposed for face recognition and progress is made. But still many challenges remains in it due to very small person to person variations and variations arising due to illumination, pose, expression and many other factors.

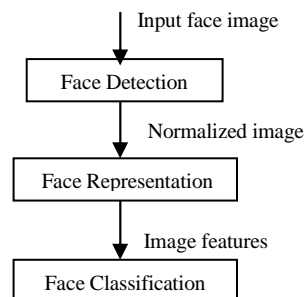


Figure 1. Typical face recognition system.

Basically, in face recognition, there are three main stages: face detection, face representation and face classification. The most important stage is face representation shown in Fig. 1. The key for the successful face recognition is to get internal representation from the normalized face images. Image representation consists of two procedures: face design and feature extraction.

Face design generates a face descriptor from one face image using some signal processing technique (e.g., Gabor wavelet [4], Local binary pattern (LBP) [1]). And feature extraction generates low-dimensional features by applying subspace analysis (e.g., Principal component analysis (PCA) [7], linear discriminant analysis (LDA) [2]).

In earlier years, geometrical features (e.g., nose width and length, mouth position and chin shape) and image template were widely used for feature design. But they are easily affected by variation in facial appearance. Later on, feature design done in frequency domain or wavelet domain attracted much attention for face recognition, such as discrete cosine transform (DCT) [12], discrete wavelet transform (DWT) [3], and Gabor wavelet [4], [5]. But the face representation using Gabor wavelet is well known and more successful. Recently, few good methods like LBP, local Gabor binary pattern (LGBP) [9], and histogram of Gabor phase pattern (HGPP) [8] are proposed which are called local Gabor pattern in this paper.

In this paper a novel approach for face recognition using 2-D Gabor wavelet, LBP and LXP for feature extraction and BFLD for feature dimension reduction is proposed.

The rest of the paper is organized as follows: Section 2 gives the related work. Proposed method is explained in Section 3. Experimental results are reported in Section 4 and conclusion is given in Section 5.

2. RELATED WORK

In this section, we firstly describe Gabor wavelet representation, LBP and LGXP respectively in 2-A, 2-B and 2-C and comparison between local patterns in 2-D.

2.1. Gabor Wavelet Representation

It was originally introduced by Dennis Gabor for 1-D signals and Daugman extended the Gabor filter for 2-D. The Gabor filters are band pass used for feature extraction. Gabor filters similar to STFT or windowed Fourier transform, have both frequency-selective and orientation-selective and have optimal joint resolution in spatial and frequency domain.

The 2-D Gabor filter is sinusoidal plane of particular frequency and orientation, modulated by a Gaussian envelope. Typical Gabor features, such as Gabor feature space consists of response calculated by Gabor filters at several different orientations and scales (frequencies): a filter bank. A bank of filters is used with different orientations so as to extract frequency information and hence the features at different orientations, since all facial features are not present at same orientation. Scaling is done at each orientation so as to get maximum frequency information at each orientation i.e., orientation and scaling helps in extracting maximum frequency information.

A 2-D Gabor kernel is given by,

$$\mu_{\mu,\nu}(z) = \frac{\|k_{\mu,\nu}\|^2}{\sigma^2} e^{-(\|k_{\mu,\nu}\|^2 \|z\|^2 / 2\sigma^2)} [e^{ik_{\mu,\nu}z} - e^{-\sigma^2/2}] \quad (1)$$

where μ and ν defines the orientation and scale of Gabor kernels, $z = (x, y)$, $\|\cdot\|$ denotes the norm operator and wave vector $k_{\mu,\nu}$ is defined as follows:

$$k_{\mu,\nu} = k_\nu e^{i\phi_\mu} \quad (2)$$

where $k_\nu = k_{max}/f^\nu$ and $\phi_\mu = \pi\mu/8$. k_{max} is the maximum frequency and f is the spacing factor between the kernels in frequency domain.

A filter bank consisting of several filters need to be used because relationships between responses provide the basis for distinguishing objects. The selection of discrete rotation angles is such that the orientation must be spaced uniformly.

$$\phi_\mu = \frac{2\pi\mu}{n}, \quad \mu = \{0, 1, \dots, n-1\} \quad (3)$$

where $\phi\mu$ is μ^{th} orientation and μ is the total number of orientations to be used. The computations can be reduced to half since angle of response $[\pi 2\pi]$ are complex conjugates on responses on $[0 \pi]$ in case of real valued input.

Frequency selection is given by,

$$k_v = f^{-v}k_{max} \quad , v = \{0,1,\dots,m-1\} \tag{4}$$

Useful values for f includes $f = 2$ for octave spacing and $f = \sqrt{2}$ for half octave spacing.

The Gabor kernels in (1) all are self-similar since they can be generated from one kernel, the mother wavelet, by scaling and rotation via wave vector $k_{\mu,v}$. Each kernel is a product of a Gaussian envelope and complex plane wave, while the first term in square brackets in (1) determines the sinusoidal part of the kernel and the second term is used to get zero DC response i.e., make Gabor filter insensitive to background luminance level σ determines the ratio of Gaussian window width to wavelength.

Gabor wavelets of five different scales $v = \{0,1,2,3,4\}$, and eight different orientations $\mu = \{0,1,2,3,4,5,6,7\}$ are used for feature extraction. Therefore, a filter bank consists of 40 filters with half octave spacing in radial direction and one octave spatial bandwidth, for $\sigma = 2\pi$, $k_{max} = \pi$, and $f = \sqrt{2}$.

2.2. Local Binary Patterns (LBP)

The LBP operator assigns a label to every pixel of an image by thresholding the 3×3 neighbourhood of each pixel with the center pixel value and considering the result as a binary number. For example, as shown in Fig. 2, “11010011” is the designed pattern of the center pixel. By applying the LBP.

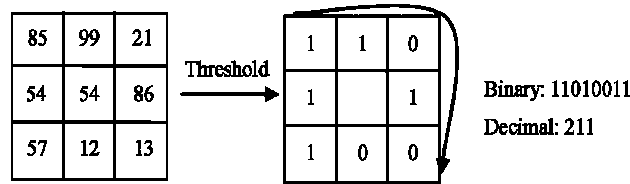


Figure 2. LBP operator define din3 neighbourhood.

Operator to one facial image, one pattern map can be computed. Then, the pattern map is divided into many block and then histogramis computed in each block and concatenated together to form the description of the input facial image [1].

2.3. Local Gabor XOR patterns (LGXP)

The basic idea of this method is that, as shown In Fig. 3, the phases are firstly quantized into different ranges and then LXP operator is applied to the quantize phases of the central pixel and of each its

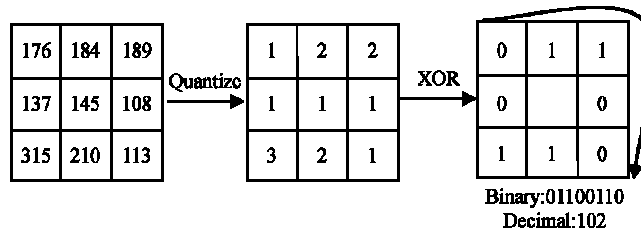


Figure 3. Example of the encoding method of LGXP where the phase is quantized into 4 ranges

Finally, the resulting binary labels are concatenated together as the local pattern of the central pixel.

2.4. Comparison with Other Local Gabor Pattern

There are various ways to get local Gabor patterns.The real and imaginary part of Gabor followed by LXP operator gives Re LGPP and Im_LGPP [8] respectively. The magnitude part of Gabor followed by LBP give LGBP_Mag [9] and phase part of Gabor followed byboth LBP and LXP gives LGBP_Pha[10] and LGXP respectively.

3. PROPOSED METHOD

Face recognition system is shown in Fig.4 consist of face detection, feature extraction and face classification. In face detection, all the face images are aligned based on the manually located eye centers provided by the original database, and then normalized to 80×88 pixels. For feature extraction Gabor filters and then local binary patterns(i.e., LGBP and LGXP) are used.

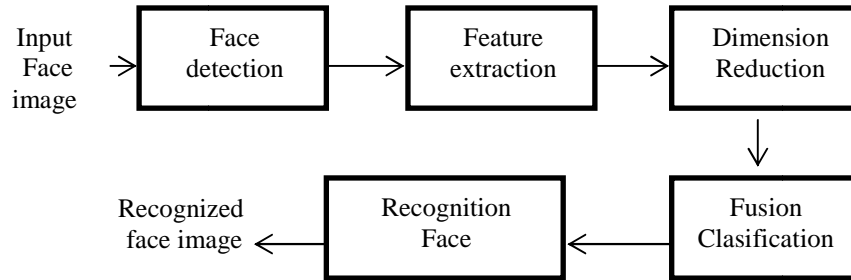


Figure 4. Blocked diagram of face recognition system

For a feature extraction, Gabor kernel convolved with the input image.

$$H(z) = \psi_{\mu,\nu}(z) * I(z) \tag{5}$$

where $H(z)$ is the convolution result, $\psi_{\mu,\nu}(z)$ is the Gabor kernel, $I(z)$ is input image, $*$ is convolution operator and $z = (x, y)$.

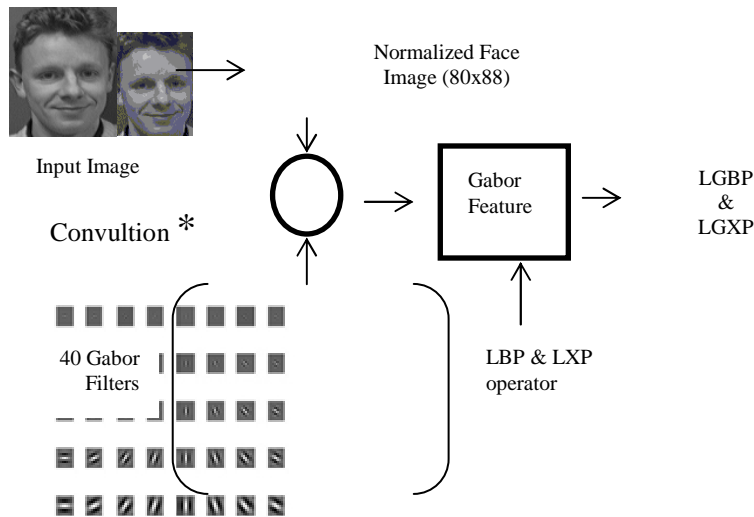


Figure 5. Steps involved in feature extraction

Then LBP and LXP operator operates on different Gabor parts (i.e., real, imaginary, magnitude and phase) which gives LGBP and LGXP shown in Fig.5.

The proposed LGXP descriptor can be directly applied to face recognition system by using similarity measurement. However, this is not good enough since the feature dimension (i.e., $m \times 40 \times 2^p$) is very high due to multiple Gabor filter (e.g., 40 in this study). In theory, to reduce dimensionality, we can apply FLD directly; but, in case of so high-dimensional feature, FLD suffers from heavy “small sample size (SSS)” problem. So, further we present block-based FLD (BFLD) approach.

The basic idea of BFLD is firstly to divide the high-dimensional LGXP descriptor into multiple

feature segments (corresponding to different spatial blocks in the face image), then apply FLD to each segment, and finally combine the decisions of all the block-wise FLD. By such a “divide and conquer” strategy, the SSS problem is greatly weakened since the dimensionality of the input feature for each FLD is much lower.

Fig.6. Flow chart of the BFLD feature extraction approach

Figure 5 illustrates the flow chart of the BFLD approach. Briefly speaking, for each face image, we firstly calculate its multiple LGXP maps. Then, we divide these pattern maps into multiple non-overlapping blocks and then we take histogram of each block and concatenate and calculate the block based representations. Based on the training set, we learn the FLD matrices to calculate the low-dimensional features for each block.

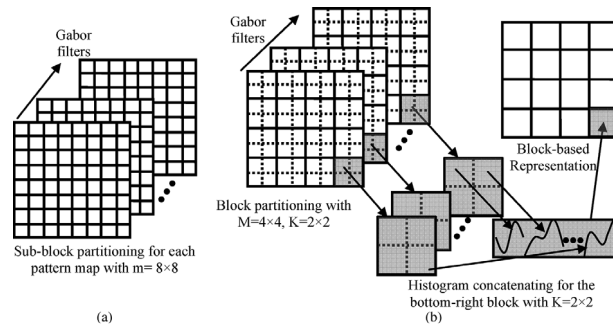


Figure 7. Fusion of LGBP_Mag and LGXP. (a) Feature-level fusion. (b) Score-level fusion.

The block partition strategy shown in Fig. 7(a) for LGXP and in Fig. 7(b) for BFLD approach. In LGXP the pattern map is directly divided into m sub-blocks but; while in BFLD pattern map divided in M blocks and each block partitioned into K sub-blocks and better representation is obtained using only one histogram.

At last, fusion of LGBP_Mag and LGXP required. The two fusion approaches are described in details as follows.

1. **Feature-level fusion.** As shown in Fig. 8(a), for the i^{th} block, we represent it as one vector by concatenating its LGBP_Mag histograms and LGXP histograms. Then by using BFLD approach calculate low-dimensional feature vector F_i . For the Gallery block I_i^g and its corresponding probe block I_i^p , the similarity between them is calculated as follows:

$$S(I_i^g, I_i^p) = sim(F_i^g, F_i^p) = \frac{F_i^g \cdot F_i^p}{\|F_i^g\| \cdot \|F_i^p\|} \quad (6)$$

2. **Score-level Fusion.** As shown in Fig. 8(b), from the two sequences of i^{th} block, $H_{LGBP_Mag,i}$ and $H_{LGXP,i}$, we respectively extract their low-dimensional FLD features, $F_{LGBP_Mag,i}$ and $F_{LGXP,i}$. Then we respectively compute two similarities between the Gallery block I_i^g and its corresponding probe block I_i^p namely $S_{LGBP_Mag,i}$ and $S_{LGXP,i}$. Finally, these two similarities are fused together according to weighted sum rule,

$$S(I_i^g, I_i^p) = w \cdot S_{LGBP_Mag,i} + (1 - w) \cdot S_{LGXP,i}$$

where w denote the weight of LGBP_Mag and varies within $[0,1]$

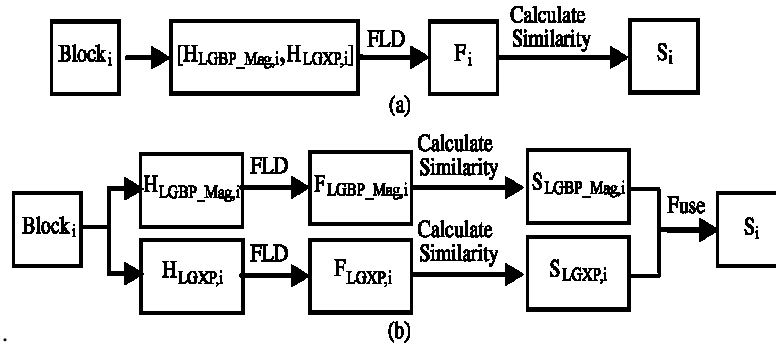


Figure 8. Fusion of LGBP_Mag and LGXP. (a) Feature-level fusion. (b) Score-level fusion.

The similarity between the Gallery and Probe face images is calculated by fusing the similarities of corresponding blocks according to the sum rule [13].

$$S(I^g, I^p) = \frac{1}{M} \sum_{i=1}^M S(I_i^g, I_i^p) \tag{7}$$

In face classification, for recognizing the input unknown face image is usually classified as the face which is most similar to input one, if the maximal similarity occurs face is recognized.

4. EXPERIMENTAL RESULTS

In this paper the FERET database is used. For details refer [6]. In our experiments, based on standard gallery (1,195 images of 1,195 subjects), we test the recognition rate of our approaches on the four probe sets: Fb (1,195 images of 1,195 subjects), Fc (194 images of 194 subjects), Duplicate I (abbreviated as “DupI”, 722 images of 243 subjects) and Duplicate II (abbreviated as “DupII”, 722 images of 243 subjects). All face images are normalized to 80×88 pixels and the size of Gabor filter window is set to 32×32 pixels.

Table 1. Recognition Rate with Local Gabor Pattern

Methods	FERET Probe Sets			
	Fb	Fc	DupI	DupII
LGBP_Mag	96%	96%	74%	70%
LGBP_Pha	97%	97%	80%	79%
Re_LGPP	98%	99%	80%	78%
Im_LGPP	98%	99%	76%	73%
LGXP	98%	100%	82%	83%

Table 2. Recognition Rate Combination With BFLD

Methods	FERET Probe Sets			
	Fb	Fc	Dup I	Dup II
LGBP_Mag+BFLD	99%	99%	91%	91%
LGBP_Pha+BFLD	99%	99%	88%	86%
Re_LGPP+BFLD	99%	100%	91%	87%
Im_LGPP+BFLD	99%	100%	90%	88%
LGXP+BFLD	99%	100%	92%	91%

Table 3. Recognition Rate With Fusing Different Gabor Parts

Methods	FERET Probe Sets			
	Fb	Fc	Dup I	Dup II
S[LGBP_Mag+LGBP_Pha]	99%	99%	92%	92%
S[Re_LGPP+Im_LGPP]	99%	100%	92%	89%
S[LGBP_Mag+Re_LGP]P	99%	99%	93%	91%
S[LGBP_Mag+LGXP]	99%	99%	93%	92%
S[LGBP_Mag+LGXP]	99%	99%	94%	93%

The results of all experiments are shown in Table 1, 2 and 3. First, the proposed LGXP method performs best in case of Fb and Fc but not for DupI and Dup II. The interesting improvement can be achieved in second method i.e., BFLD with local Gabor patterns especially in case of Dup I and Dup II. The third method fusion of LGBP_Mag and LGXP leads to best improvement and specially for $S[LGBP_{Mag} + LGXP]$.

5. CONCLUSION

In this paper, we have mainly work on Gabor phase information, as well as its fusion with Gabor magnitude. By using local patterns we encode the Gabor phase called LGXP. Then we introduce BFLD and studied the fusion methods of different local patterns of Gabor features. These methods achieve better or comparable results than the best known ones.

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