Are Gabor Phases Really Useless for Face Recognition?

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Abstract

Gabor feature has been recognized as one of the best representations for face recognition. Traditionally, only the magnitudes of the Gabor coefficients are thought of valuable for face recognition, and the phases of Gabor features are deemed to be useless and always discarded directly by almost all researchers in face recognition community. However, in this paper, we show that this observation should be re-considered. By encoding Gabor phases through Local Binary Pattern (LBP) and spatial histograms, we have achieved very encouraging recognition rate comparable with that of Gabor magnitude based methods. And we also show that the Gabor phases are quite compensatory to the magnitude information, since higher classification accuracy is achieved by combining Gabor phases and magnitudes. All these observations suggest that more attention should be paid to traditionally abandoned Gabor phases for face recognition.

1. Introduction

Face recognition (FR) has attracted more and more attention for both its scientific challenges and its wide potential applications. Much progress has been made in the last decade as surveyed in [1]. However, the general problem of FR remains to be solved, since most of the systems to date can only successfully recognize faces when images are obtained under constrained conditions. Their performance will degrade abruptly when faces images are captured under varying lighting sources, viewpoints, expressions, and partial occlusion.

The performance of a face recognition system depends not only on the classifier, but also on the representation of the face patterns. Generally speaking, a good representation should have such characteristics as small within-class variation, large between-class variation, and being robust to transformations without changing the class label. Furthermore, its extraction should not depend much on the manual operation. For these reasons, Gabor wavelets have been widely accepted by researchers in face recognition community [2,3,4,5], because the kernels of Gabor wavelet are similar to the 2D receptive field profiles of the mammalian cortical simple cells and exhibit desirable characteristics of spatial locality and orientation selectivity. Previous works on Gabor features have also demonstrated excellent performance. Typical methods include the Dynamic Link Architecture (DLA) [2], Elastic Bunch Graph Matching (EBGM) [3], Gabor Fisher Classifier (GFC) [4], and AdaBoosted GFC (AGFC) [5].

More recently, by combining Gabor feature with the Local Binary Patterns [6], Zhang et al [7] has proposed Local Gabor Binary Pattern by introducing Gabor transform before LBP. They had reported impressively improved performance when compared with the pure LBP and GFC. And LGBP has reported the best results on FERET database by far.

However, we find it a little strange that, compared with the successful application of Gabor phase in Iris recognition [8], the Gabor phases are deemed to be useless and always discarded directly by almost all researchers in face recognition community. Only the magnitudes of the Gabor coefficients are thought of valuable for face recognition as is done in [4,5,7]. We must note that, in DLA and EBGM, Gabor phases do be exploited. But we feel that it is actually employed to localize facial landmarks by using the displacement sensitivity of Gabor phases. So, are Gabor phases really useless for face recognition?

In this paper, by encoding Gabor phases through Local Binary Pattern (LBP) and spatial histograms, we have achieved very encouraging recognition rate comparable with that of Gabor magnitude based methods, which shows that Gabor phases also contribute a great deal to the discrimination of different faces. And we also show that the Gabor phases are quite compensatory to the Gabor magnitude, since higher classification accuracy is achieved by combining Gabor phases and magnitudes. All these observations suggest that more attention should be paid to traditionally abandoned Gabor phases for face recognition.

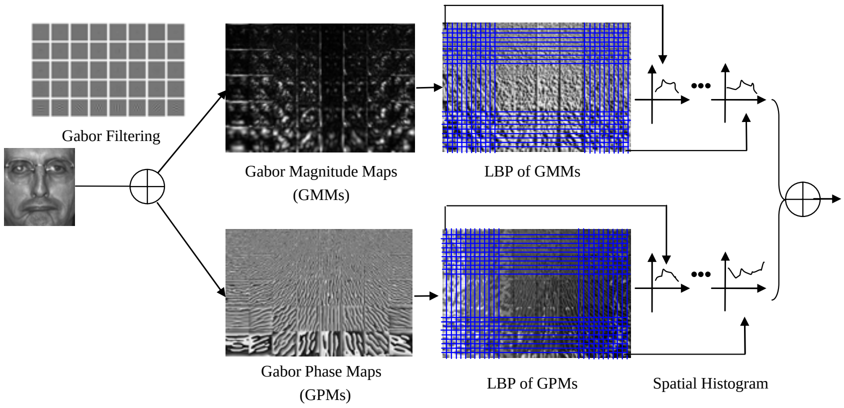


Figure 1**. Framework of the face representation extraction using the proposed ELGBP method.**

2. Enhanced LGBP for Face Recognition

We describe in this section how the Gabor phase, discarded directly by most previous work on Gabor for face recognition due to its sensitivity to locations [2, 3], is exploited to combine with Gabor magnitude to further improve the performance of LGBP.

The framework of the proposed ELGBP is illustrated in Fig.1. For any given normalized face image, it is first convoluted with 40 Gabor filters (5 scales and 8 orientations). So, 40 Gabor magnitude maps and 40 Gabor phase maps, both with the same size as the original face image, are obtained. These maps are further processed by LBP respectively, which results in 80 LBP images of all the magnitude and phase maps. Then, LBP images are divided spatially to multiple sub-windows and histograms are estimated from them respectively to form the final representation of the input face image. Finally, classification is achieved by matching all these histograms using the histogram intersection as the similarity measurement. The difference of the method from Zhang et al's work is the using of the phase.

2.1 Local Gabor Binary Patterns (LGBP)

For the purpose of completeness, this section briefly introduces the techniques in Zhang et al's LGBP method. Actually, one can get its basic idea by ignoring the lower part (i.e, the use of phase) of Fig.1 and keeping only the upper part exploiting magnitude. LGBP can be regarded as a harmonious combination of Gabor feature with LBP. Its main merit over LBP lies in its capacity of modeling local features of varying orientations and scales, which is provided by the Gabor transform.

The Gabor filters used in LGBP (and ELGBP) are as follows:[4,5,7]

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

where μ and ν define the orientation and scale of the Gabor filters, $z=(x,y)$, $\|\cdot\|$ denotes the norm operator, and the wave vector $k_{\mu,\nu} = k_\nu e^{i\phi_\mu}$, where $k_\nu = k_{\max}/\lambda^\nu$ and $\phi_\mu = \pi\mu/8$. λ is the spacing factor between filters in the frequency domain. Convolving the image with each of the 40 Gabor filters can then generate the Gabor features. In LGBP, only the magnitude value at each image point is kept for further processing.

LBP is another key technique, which is operated on the Gabor magnitude in LGBP. The LBP operator extracts the local variance feature of an image, such as the edge and the spot which are important to classify different face images. The original LBP operator labels the pixels of an image by thresholding the 3×3-neighborhood of each pixel $f_p(p=0,1,\ldots,7)$ with the center value f_c and considering the result as a binary number [6]:

$$S(f_p - f_c) = \begin{cases} 1, & f_p \geq f_c \\ 0, & f_p < f_c \end{cases}. \qquad (2)$$

Then, by assigning a binomial factor 2^p for each $S(f_p - f_c)$, the LBP pattern at the pixel is achieved as:

$$LBP = \sum_{p=0}^{7} S(f_p - f_c)2^p. \qquad (3)$$

The spatial histogram is conducted on the 40 LBP images of Gabor magnitude maps. Finally, one obtains the final face representation as:

$$\Re = \left(\mathrm{H}^m_{0,0,0},\cdots,\mathrm{H}^m_{0,0,R-1},\mathrm{H}^m_{0,1,0},\cdots,\mathrm{H}^m_{0,1,R-1},\cdots,\mathrm{H}^m_{7,4,R-1}\right), \qquad (4)$$

where the H superscript m means magnitude, the three items of the H subscript denotes the orientation, scale, and region index of the spatial sub-window respectively, and $H^m_{\mu,v,r}$ means the histogram extracted from the *r*-th region of the LBP image of Gabor magnitude maps computed from the Gabor filter with the μ-th orientation and the *v*-th scale.

Finally, faces are compared by matching the face representation using the histogram intersection of all the spatial histograms:

$$S(\Re_1,\Re_2)=\sum_{\mu=0}^{7}\sum_{v=0}^{4}\sum_{r=0}^{R-1}W_{\mu,v,r}\Psi\left(H^1_{\mu,v,r},H^2_{\mu,v,r}\right), \quad (5)$$

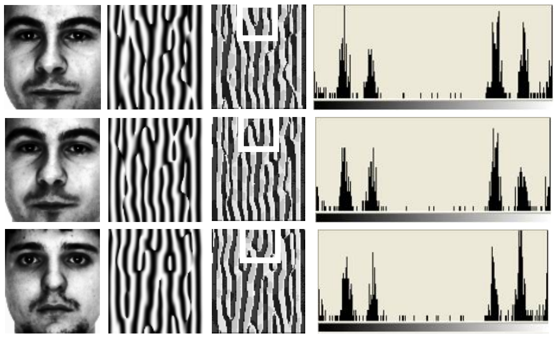
where *R* is the total number of regions, *W* is the weight for the (μ,*v,r*)-th histogram, and Ψ denotes the intersection of two spatial histogram. In [7], Zhang et al proposed a Fisher's linear discriminant methods to set different weights for spatial histograms.

2.2 ELGBP: Exploit Phase Information

When a face image is convoluted with the *j*-th Gabor wavelet, for each image position, a complex Gabor wavelet coefficient, $G_j = A_j \cdot \exp(i\varphi_j)$, with one magnitude item A_j, and one phase item φ_j, can be obtained. It is well known that the magnitudes vary slowly with spatial position, while the phases rotate in some rate with position, as can be seen from the examples in Fig. 2(b). Due to this rotation, the phases taken from image points only a few pixels apart have very different values, although representing almost the same local feature. This can cause severe problems for object matching, and it is just the reason that most previous works make use of only the magnitude for face classification [3,4,5,7].

However, the Gabor phase is not worthless, considering that phase information can discriminate between patterns with similar magnitudes, should they occur. Considering the slow varying of the magnitude, we argue that the phase provides more detailed information about the local image feature. Therefore, the phase can be compensatory to magnitude if one can exploited it elaborately avoiding its sensitivity to location varying. A typical successful application of Gabor phase is the phase-quadrant demodulation coding method proposed by Daugman for iris recognition [8].

In this paper, again we turn to LBP, which can model neighborhood variations, combining with the spatial histogram modeling, which can model the holistic distribution of a relatively larger local region. By modeling a local region rather than single pixel, both LBP and spatial histogram can inhibit the spatial-varying effect of phase information. Figure 2 has illustrated the characteristics of this procedure. As can be seen from Fig. 2, the phase maps, their LBP results, as well as the spatial histogram, of the same person (the first two rows) look more similar than those of different persons.



(a) (b) (c) (d)

Figure 2. Illustration of Gabor Phase map and its LBP results (a) Input Image; (b) Gabor Phase map of one Gabor wavelet convoluted with the input image; (c) LBP results of the phases in b; (d) one spatial histogram of phase LBP.

So, a face image is finally represented as follows:

$$\Re = \left(\Re^m, \Re^p\right) \quad (6)$$

$$\Re^m = \left(H^m_{0,0,0},\cdots,H^m_{0,0,R-1},H^m_{0,1,0},\cdots,H^m_{0,1,R-1},\cdots,H^m_{7,4,R-1}\right) \quad (7)$$

$$\Re^p = \left(H^p_{0,0,0},\cdots,H^p_{0,0,R-1},H^p_{0,1,0},\cdots,H^p_{0,1,R-1},\cdots,H^p_{7,4,R-1}\right) \quad (8)$$

where $\Re^m$ and $\Re^p$ are respectively the spatial histograms of Gabor magnitudes and phases. Please refer to Equ.4 for the meaning of other symbols.

In turn, the similarity between two ELGBP face representations is computed by combining the magnitude and phase similarity:

$$S(\Re_1,\Re_2) = S^m(\Re_1,\Re_2) + S^p(\Re_1,\Re_2) \quad (9)$$

$$S^m(\Re_1,\Re_2) = \sum_{\mu=0}^{7}\sum_{v=0}^{4}\sum_{r=0}^{R-1} W^m_{\mu,v,r} \cdot \Psi\left(H1^m_{\mu,v,r}, H2^m_{\mu,v,r}\right) \quad (10)$$

$$S^p(\Re_1,\Re_2) = \sum_{\mu=0}^{7}\sum_{v=0}^{4}\sum_{r=0}^{R-1} W^p_{\mu,v,r} \cdot \Psi\left(H1^p_{\mu,v,r}, H2^p_{\mu,v,r}\right). \quad (11)$$

Note that the same Fisher separation criterion weighting method as used in LGBP [7] can be directly taken to assign different weights for varying spatial histograms.

3. Experiments

The FERET face database is used to validate the proposed method according to the standard FERET evaluation protocol, which has exactly defined the gallery and probe sets. In our experiments, we strictly evaluate all the methods based on the standard gallery (1196 images of 1196 subjects) and four probe sets, fafb(1195 images), fafc (194 images), dup.I (722 images), and dup.II (234 images). Please refer to [9] for details about the FERET evaluation protocol. Note that 1002 frontal images of 429 subjects, a subset of the FERET training CD, are used as the training set for methods that need a training stage.

Using the standard FERET evaluation protocol [9], we compare the performance of ELGBP with that of the LGBP [7], the GFC[4], as well as the best FERET97 [9] results and latest ECCV04 [6] results. Since (E)LGBP with uniform weights needs no training set, we directly evaluate the method by matching each image in the four standard probe sets against all the images in the gallery set containing 1195 subjects. While for the weighting version of (E)LGBP, we also compute the weights based on the standard FERET training CD. The comparison results are given in Table 1, Note that, in the title of the methods of the table, the "Mag" means "magnitude" and "Pha" means "phase".

From Table 1, one can see that, although the performance of LGBP using the phase only (abbr. as LGBP_PhaOnly) is indeed a little worse than that of LGBP using magnitude only (abbr. as LGBP_MagOnly), it performs reasonably well and comparable to the results reported in ECCV04 paper [6]. Furthermore, when it is classified using weighted method, titled by LGBP_PhaOnly_W, its performance is even much better than ECCV04 results. This indicates that the Gabor phase also contributes a great deal to face classification. We think this point should be noticed by face recognition researchers.

Table 1. The rank-1 recognition rates of different algorithms on the FERET probe sets.

Methods	FERET Probe Sets			
	fafb	fafc	Dup.I	Dup.II
GFC [4]	0.95	0.84	0.67	0.61
Results FERET'97[9]	0.96	0.82	0.59	0.52
Results in ECCV04[6]	0.97	0.79	0.66	0.64
LGBP_MagOnly[7]	0.94	0.97	0.68	0.53
LGBP_MagOnly_W[7]	**0.98**	**0.97**	0.74	0.71
LGBP_PhaOnly	0.93	0.92	0.65	0.59
LGBP_PhaOnly_W	0.96	0.94	0.72	0.69
ELGBP (Mag + Pha)	0.97	0.96	**0.77**	**0.74**
ELGBP (Mag + Pha)_W	**0.99**	**0.96**	**0.78**	**0.77**

One can also notice that, the ELGBP, that is, the combination of the phase LBP with magnitude LBP, generally outperforms all other methods. This observation further validates the value of the phase, and indicates that the phase is a useful compensatory to the magnitude, at least it is true when they are coded by LBP and spatial histogram.

4. Conclusions

This paper has discussed whether Gabor phases are really useless or not for face classification. By encoding Gabor phases through Local Binary Pattern (LBP) and spatial histograms, we have achieved very encouraging recognition rate comparable with that of Gabor magnitude based methods, which shows that Gabor phases also contribute a great deal to the discrimination of different faces. And we also show that the Gabor phases are quite compensatory to the Gabor magnitude, since higher classification accuracy is achieved by combining Gabor phases and magnitudes.

The results of this paper suggest that Gabor phases have been traditionally underestimated in most face recognition techniques, and more attention should be paid to traditionally abandoned Gabor phases for face recognition.

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