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Are Gabor phases really useless for face recognition?

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Abstract Gabor features have been recognized as one of the best representations for face recognition. Usually, only the magnitudes of the Gabor coefficients are thought of as being useful for face recognition, while the phases of the Gabor features are deemed to be useless and thus usually ignored by face recognition researchers. However, in this paper, our findings show that the latter should be reconsidered. By encoding Gabor phases through local binary patterns and local histograms, we have achieved very impressive recognition results, which are comparable to those of Gabor magnitudes-based methods. The results of our experiments also indicate that, by combining the phases with the magnitudes, higher accuracy can be achieved. Such observations suggest that more attention should be paid to the Gabor phases for face recognition.

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1 Introduction

More attention has been paid to face recognition due to its scientific challenges and wide potential applications. Much progress has been made in the last decade [1]. However, most of the systems to date can only successfully recognize faces when images are obtained under controlled conditions. Their performance will decline abruptly when images are taken under varying lighting conditions, poses, expressions, aging, etc. [2, 3].

The performance of a face recognition system depends not only on the classifier, but also on the face representation. Generally, a good face representation should have the characteristics such as small within-class variation, large between-class variation, and resistance to transformations. In addition, feature extraction should depend on manual operation as little as possible, i.e. the representation should be insensitive to imprecise alignment, since misalignment may often occur for fully automatic face recognition systems [4].

In recent years, Gabor wavelets have been widely used for face representation by face recognition researchers [5–9], because the kernels of the Gabor wavelets are similar to the 2D receptive field profiles of the mammal cortical simple cells, which exhibits desirable characteristics of spatial locality and orientation selectivity. In addition, the results of Gabor transform, i.e. the coefficients of the convolution, represent the information in a local face region, which should be more effective than isolated pixels. Previous works on Gabor features have also demonstrated impressive results for face recognition. Typical methods include the dynamic link architecture (DLA) [5], elastic bunch graph matching (EBGM) [6], Gabor Fisher classifier (GFC) [7], and AdaBoosted GFC (AGFC) [8]. Gabor features are also used for gait recognition and gender recognition recently [10, 11].

However, we notice that in most previous work using Gabor feature, only the magnitudes of the Gabor coefficients are used for face recognition, while the Gabor phases are considered useless and ignored directly. This is in sharp contrast with the successful application of Gabor phases in iris recognition [12]. Especially, it is worth noting that, in EBGM, Gabor phases are used not for recognition, but for the localization of facial landmarks by making use of the sensitivity of Gabor phases to its displacement. It is well known that Gabor phases taken from image points of only a few pixels apart are very different, although representing almost the same local features [6]. In other words, Gabor phases are sensitive to local variations or misalignment, which can result in severe problems in the matching of two face images. This sensitivity may account for the rare usage of Gabor phases for face recognition. Thus, one question arises: are Gabor phases really useless for face recognition?

In this paper, our findings show that, though Gabor phases are sensitive to local variations, they can discriminate between patterns with similar magnitudes, i.e. they provide more detailed information about the local image features. Therefore, the Gabor phases can work comparably well with the magnitudes, as long as its sensitivity to misalignment and local variations can be compensated carefully.

In our previous work [13], we proposed to represent face images using the local Gabor binary patterns (LGBP), which combines Gabor magnitudes with local binary patterns (LBP) operator [14]. Improved results are achieved when compared with the LBP and the GFC. Since face representation with LGBP is based on local histograms, which are insensitive to local variations [15], similarly local histograms of LGBP can be used to suppress the sensitivity of Gabor phases to local variations. By encoding Gabor phases through LBP and local histograms, we have achieved very impressive recognition rates comparable with those of Gabor magnitudes-based methods, which shows that Gabor phases are also effective in the discrimination of different faces.

The remaining part of this paper is organized as follows: Sect. 2 will cover detailed description of face representations with LGBP based on Gabor phases and with the enhanced LGBP (ELGBP) by integrating phases and magnitudes. Then, Sect. 3 describes the face recognition methods based on LGBP with Gabor phases. Experimental results are given in Sect. 4, followed by the conclusion in Sect. 5.

2 Enhance LGBP by integrating Gabor phases for face representation

In this section, we describe how Gabor phases are combined with Gabor magnitudes based on the LGBP method. For completeness, first, we briefly introduce the Gabor wavelets for face representation as well as the LBP operator; and subsequently, we show how LGBP is enhanced by integrating Gabor phases.

2.1 Gabor wavelets for face representation

The 2D Gabor wavelets can be defined as follows [5]

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

where v and μ define the scale and the orientation of the Gabor wavelets, respectively; $z = (x, y)$; $\|\cdot\|$ denotes the norm operator; and $k_{v,\mu} = k_v e^{i\varphi_\mu}$ with $k_v = k_{\max}/\lambda^v$, ϕ_μ the orientation parameter and λ the spacing factor between wavelets in the frequency domain.

The Gabor transform of a face image can be obtained by convolving the face image with the Gabor wavelets. Given an input face image $f(x, y)$, its convolution with a Gabor wavelet $\psi_{v,\mu}(x, y)$ can be defined as

$$\mathrm{O}_{v,\mu}(x,y) = f(x,y) * \psi_{v,\mu}(x,y), \quad (2)$$

where * denotes the convolution operator.

2.2 Local binary patterns

The original local binary patterns (LBP) operator, first proposed by Ojala et al. [16], is a powerful method for texture description [17]. The basic version of the LBP operator labels the pixels of an image by calculating the neighborhood of each pixel with the center value through Eq. 3 and taking into account the result as a binary string. As shown in Fig. 1a, if the eight neighbors of the center

0	1	2
7		3
6	5	4

(a)

2^0	2^1	2^2
2^7		2^3
2^6	2^5	2^4

(b)

Fig. 1 The neighborhood indices and weights: **a** The neighborhood index p; **b** the corresponding weights pixel located at (x_c, y_c) are (x_p, y_p), $p = 0,1,\cdots,7$, the LBP pattern at (x_c, y_c) is calculated as

$$\mathrm{LBP}(x_c, y_c) = \sum_{p=0}^{7} S\big(f(x_p, y_p) - f(x_c, y_c)\big)2^p, \tag{3}$$

where $S(A) = \begin{cases} 1, & A \geq 0 \\ 0, & A < 0 \end{cases}$.

In the binary LBP string, the pth bit stands for the order relationship between the center pixel and its pth neighbor. The LBP operator codifies the occurrence of some micro-patterns, such as dots, edges, corners, etc.

2.3 Encoding Gabor phases by LBP

When a face image is convoluted with the (v, μ)th Gabor wavelet, for each image position, a complex Gabor wavelet coefficient can be obtained

$$\mathrm{O}_{v,\mu} = A_{v,\mu} \cdot \exp\big(i\varphi_{v,\mu}\big) \tag{4}$$

where the item $A_{v,\mu}$ denotes the magnitude and $\phi_{v,\mu}$ represents the phase part. These two parts have quite different properties. The magnitudes vary slowly with spatial position, i.e. the magnitudes of the neighboring pixels are very similar. Therefore, magnitude is resistant to local variations caused by expressions and imprecise alignment. This is the main reason why Gabor magnitudes are used widely in many face recognition systems. On the contrary, Gabor phases are highly responsive to the changes in facial position. Because of such sensitivity, the phases taken from image points only a few pixels apart have very different values, although representing almost the same local feature [6]. This can cause severe problems in feature-matching, which explains why most previous works only use magnitudes for face classification.

As such, in our previous work, local Gabor binary patterns (LGBP) [13], we only used the magnitudes and discarded the phase part. The LGBP operator is defined as

$$\mathrm{LGBP}^{m}_{v,\mu}(x_c, y_c) = \sum_{p=0}^{7} S\big(A_{v,\mu}(x_p, y_p) - A_{v,\mu}(x_c, y_c)\big)2^p. \tag{5}$$

These LGBP labels are then encoded further to local histograms, which are used as the face representation for classification.

However, the success of Gabor phases in iris recognition [12] inspires us to reevaluate Gabor phases for face recognition. Some intuitive tests are conducted to observe the difference between Gabor magnitudes and Gabor phases. As shown in Fig. 2, the Gabor magnitudes and phases of two face images of the same subject under different lighting conditions are visualized. In the figure, the two input example images, Fig. 2a, d, are captured under left

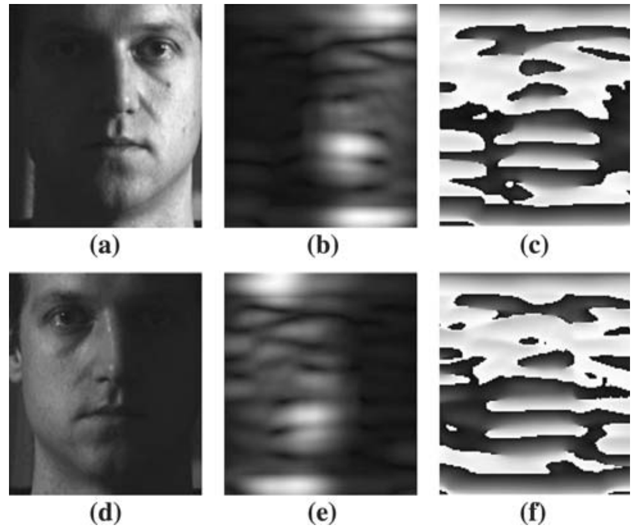

Fig. 2 The Gabor magnitudes and Gabor phases of the face images from the same subject with different illuminations: **a**, **d** Face images with different illuminations; **b**, **e** the Gabor magnitudes of (**a**) and (**d**). **c**, **f** Illustration of the Gabor phases of (**a**) and (**d**)

and right side lighting, respectively. Clearly, from Fig. 2b, e, the spectrums of the Gabor magnitudes are greatly affected by the side lighting, and some overflow can be observed in the left and right portion, respectively, due to the underexposure. In contrast, the spectrums of Gabor phases, as shown in Fig. 2c, f, keep more detailed local information, especially in the underexposure area. From these observations, we can safely conclude that Gabor phases also take rich information especially for those pixels whose Gabor magnitudes are inseparable.

The above analysis and observations make us believe that, compared with the magnitude part, the Gabor phases are also resistant to local variations and thus may result in higher accuracy in face recognition. In addition, it is well known that local histogram is a kind of descriptor robust to local variations such as affine transformation. As our previous work on LGBP also indicated the same findings, we extended LGBP by substituting the Gabor phases for the Gabor magnitudes. The LGBP operator based on Gabor phase is defined as follows:

$$\mathrm{LGBP}^{p}_{v,\mu}(x_c, y_c) = \sum_{p=0}^{7} S\big(\phi_{v,\mu,p}(x_p, y_p) - \phi_{v,\mu,c}(x_c, y_c)\big)2^p. \tag{6}$$

To discriminate the LGBP based on Gabor phases, hereinafter, the LGBP method based on Gabor magnitudes is abbreviated as "LGBP_Mag," while the LGBP method based on Gabor phases is denoted by "LGBP_Pha." In addition, their combinations are named as Enhanced LGBP (ELGBP).

2.4 Face representation combining Gabor phases and magnitudes

Similar to our previous work, i.e., the LGBP_Mag, histogram is also used to calculate the different patterns of LGBP_Pha labels. Histogram is an appropriate method for face representation due to its resistance to facial variations. However, if histogram is computed within the whole image in the LGBP_Pha domain, we will lose the spatial information of each feature, which is a key factor for face representation. To solve this problem, region-based histograms are employed, i.e. each LGBP-Pha image is spatially partitioned into multiple nonoverlapping regions with the same size, and histogram is extracted from each region. We call this method as "local histograms." A face image is finally represented as the concatenation of these local histograms:

$$\mathrm{H}^{p} = \left(\mathrm{H}^{p}_{0,0,0}, \mathrm{H}^{p}_{0,0,1}, \cdots, \mathrm{H}^{p}_{0,0,R-1}, \mathrm{H}^{p}_{0,1,0}, \cdots, \mathrm{H}^{p}_{0,1,R-1}, \cdots, \mathrm{H}^{p}_{4,7,R-1}\right), \tag{7}$$

where R is the number of regions for each LGBP_Pha image, and $\mathrm{H}^{p}_{v,\mu,r}$ denotes the histogram of the (v, μ, r)th region in the LGBP_Pha image. This is computed as

$$\mathrm{H}^{p}_{v,\mu,r}(i) = \sum_{(x,y)\in\Omega_r} \delta\left(\mathrm{LGBP}^{p}_{v,\mu}(x,y) - i\right), \quad i = 0,1,\ldots,L-1, \tag{8}$$

where $\delta(z) = \begin{cases} 1, & z = 0 \\ 0, & \text{otherwise} \end{cases}$, Ω_r denotes the rth region in the LGBP_Pha image, and L is the total number of possible labels for LGBP, i.e. the bin number of the histogram.

By modeling a local region rather than isolated pixels, both LBP and local histogram can inhibit the spatial varying effect of phase information to some degree. Therefore, both accuracy and robustness to face variations can be expected for LGBP_Pha.

Thus, face representation combining Gabor phases and magnitudes can be denoted as

$$\begin{aligned}\mathrm{H} &= (\mathrm{H}^{m}, \mathrm{H}^{p}) \\ &= \left(\mathrm{H}^{m}_{0,0,0}, \mathrm{H}^{m}_{0,0,1}, \ldots, \mathrm{H}^{m}_{4,7,R-1}, \mathrm{H}^{p}_{0,0,0}, \mathrm{H}^{p}_{0,0,1}, \ldots, \mathrm{H}^{p}_{4,7,R-1}\right).\end{aligned} \tag{9}$$

To sum up, the framework of the proposed enhanced LGBP (ELGBP), i.e., the combination of the LGBP_Pha and LGBP_Mag, is illustrated in Fig. 3. For any given normalized face image, it is first convoluted with all the 40 Gabor filters (five scales and eight orientations are used in this paper). Thus, the Gabor magnitude images and the Gabor phase images, both with the same size as the original face image, are obtained. These images are further processed by LBP, respectively, which results in 40 LGBP_Mag images and 40 LGBP_Pha images. Thereafter, LGBP_Mag and LGBP_Pha images are divided spatially to multiple subwindows, and histograms are estimated from them, respectively, to form the final representation of the input face image.

3 LGBP with Gabor phases for face recognition

This section presents how the proposed representation based on LGBP is applied to face recognition. We applied two measurements. One is the direct matching method, and the other is the region-weighting method, which attempts to emphasize the distinct significance of the different facial region.

In our paper, histogram intersection (HI) is used to measure the similarity of different histograms. One of its advantages of HI is that it does not take into account features, which only occur in one of the histograms. Thus, the variation of different images of the same subject can be reduced further. The intersection measurement of two histograms [18] can be defined as

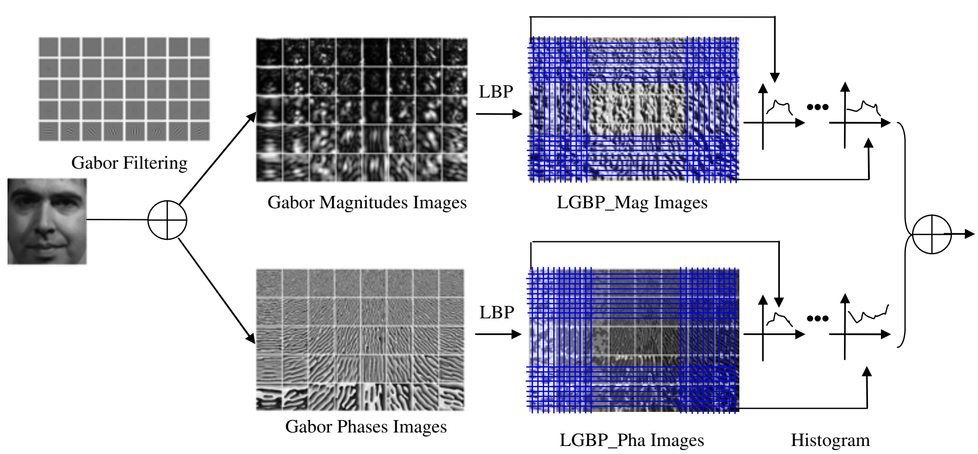

Fig. 3 Framework of the face representation extraction in the proposed ELGBP method

$$\cap(\mathbf{h}^1, \mathbf{h}^2) = \sum_{i=0}^{L-1} \min(\mathbf{h}_i^1, \mathbf{h}_i^2) \tag{10}$$

where $\mathbf{h}^1$ and $\mathbf{h}^2$ denote two histograms and L is the number of histogram bins.

Using this measurement, the similarity of two face images represented by LGBP_Mag, LGBP_Pha, and ELGBP can be calculated, respectively, as

$$\mathrm{S}(A^m, B^m) = \sum_{v=0}^{4} \sum_{\mu=0}^{7} \sum_{r=0}^{R-1} \cap\left(A^m_{v,\mu,r}, B^m_{v,\mu,r}\right), \tag{11}$$

$$\mathrm{S}(A^p, B^p) = \sum_{v=0}^{4} \sum_{\mu=0}^{7} \sum_{r=0}^{R-1} \cap\left(A^p_{v,\mu,r}, B^p_{v,\mu,r}\right), \tag{12}$$

$$\mathrm{S}(A, B) = \mathrm{S}(A^m, B^m) + \mathrm{S}(A^p, B^p), \tag{13}$$

where A^m, A^p, A and B^m, B^p, B denote LGBP_Mag, LGBP_Pha, ELGBP representation of the two face images, respectively.

The above measurement treats all the local regions equally for classification, but previous works show that some facial areas contain more discriminative information than others in distinguishing between subjects [1]. For example, the human eye is an important factor for face recognition. To take this factor into account, a weight can be assigned to each local histogram based on its contribution to the classification. In this case, the similarity of two face images represented by weighted LGBP_Mag, LGBP_Pha, and ELGBP can be defined, respectively, as

$$S'(A^m, B^m) = \sum_{v=0}^{4} \sum_{\mu=0}^{7} \sum_{r=0}^{R-1} W^m_{v,\mu,r} \cap \left(A^m_{v,\mu,r}, B^m_{v,\mu,r}\right), \tag{14}$$

$$S'(A^p, B^p) = \sum_{v=0}^{4} \sum_{\mu=0}^{7} \sum_{r=0}^{R-1} W^p_{v,\mu,r} \cap \left(A^p_{v,\mu,r}, B^p_{v,\mu,r}\right), \tag{15}$$

$$\mathrm{S}'(A, B) = \mathrm{S}'(A^m, B^m) + \mathrm{S}'(A^p, B^p), \tag{16}$$

where $W^m_{v,\mu,r}$ and $W^p_{v,\mu,r}$ denote the weights of the (v, μ, r)th region in the LGBP_Mag image and LGBP_Pha image, respectively. Correspondingly, the region-weighting versions of the above three methods are denoted by LGBP_Mag_W, LGBP_Pha_W, and ELGBP_W, respectively.

In this study, the weight for each region is learned by Fisher linear discriminant [19], which is able to discriminate different patterns better. It is generally believed that the similarities of different images from the same subject are higher than those from different subjects. Based on this observation, we define two distinct and mutually exclusive classes: Ω_b and Ω_w. The former represents the interpersonal similarities (the similarity between two local histograms extracted from two images of different subjects), while the latter represents the intrapersonal similarities (the similarity between two local histograms extracted from two images of the same subject). Then, we define $W_{v,\mu,r}$ $\left(W^m_{v,\mu,r} \text{ or } W^p_{v,\mu,r}\right)$ as follows

$$W_{v,\mu,r} = \frac{\left(m_{I(v,\mu,r)} - m_{E(v,\mu,r)}\right)^2}{S^2_{I(v,\mu,r)} + S^2_{E(v,\mu,r)}}, \tag{17}$$

where $m_{I(v,\mu,r)}$ and $S^2_{I(v,\mu,r)}$ are the mean and the variance of the intrapersonal similarities, respectively, while $m_{E(v,\mu,r)}$ and $S^2_{E(v,\mu,r)}$ are the mean and the variance of the interpersonal similarities, respectively.

4 Experiment

The FERET face database is used to validate the proposed method according to the standard FERET evaluation protocol [2], which contains a training set, a gallery, and four probe sets. A subset of the FERET training CD, containing 1,002 frontal images of 429 subjects, is used to train the face recognizer. The gallery contains a set of known individuals, which consists of 1,196 subjects with one image per subject. The probe sets contain the images of unknown individuals, and are used to test the face recognition algorithm. Among the four probe sets, the **FB** (facial expression) probe set contains 1,195 probe images taken on the same day and under the same lighting conditions as the corresponding gallery images. The **fc** probe set contains 194 images taken on the same day as the corresponding gallery images, but with a different camera and lighting condition. The duplicate I and duplicate II probe sets contain 722 and 234 duplicate (with aging variation) frontal images in the FERET face database for the gallery images.

Using the standard FERET evaluation protocol, we compared the performance of LGBP with that of the GFC [7], as well as the best FERET'97 results [2]. It should be noted that GFC_Mag denotes the original method [7], while GFC_Pha denotes the GFC method based on phases instead of magnitudes. It is worth pointing out that, for the LGBP with uniform weights, the abovementioned training set is not used, since it needs no training. Instead, we directly did tests by matching each image in the four standard probe sets against all the images in the gallery. For weighted version of the LGBP, the training set is used only for learning the weights.

The comparison results are shown in Table 1. It can be seen that the results of LGBP_Pha are comparable to those of LGBP_Mag. Especially, when LGBP_Pha is classified using the weighted method, i.e., LGBP_Pha_W, its results are better than those of FERET'97. This indicates that Gabor phases indeed contribute a great deal to face classification and should be reconsidered by face recognition researchers.

It is also important to note that, the ELGBP, i.e., the combination of LGBP_Mag and LGBP_Pha, outperforms

Table 1 The recognition rates of different methods on the FERET probe sets

Methods	FERET probe sets			
	FB	fc	Duplicate I	Duplicate II
GFC_Mag	0.95	0.84	0.67	0.61
GFC_Pha	0.89	0.72	0.65	0.56
FERET'97[a]	0.96	0.82	0.59	0.52
LGBP_Mag	0.94	0.97	0.68	0.53
LGBP_Mag_W	0.98	0.97	0.74	0.71
LGBP_Pha	0.93	0.92	0.65	0.59
LGBP_Pha_W	0.96	0.94	0.72	0.69
ELGBP	0.97	0.96	0.77	0.74
ELGBP_W	0.99	0.96	0.78	0.77

[a] Denotes that the results are from the original paper [3]

all other methods. This observation implies that the Gabor phase can be a compensation of the Gabor magnitude for face classification, at least when they are coded by LBP and local histograms.

5 Conclusion

This paper has showed that Gabor phases are useful for face recognition. By encoding Gabor phases through LBP operator and local histograms, we have achieved very impressive recognition rates, which are comparable with those of Gabor magnitudes. This indicates that Gabor phases also contribute a great deal to the discrimination of different faces. We have also shown that Gabor phase can be a compensation of the Gabor magnitude for more accurate face classification. These observations suggest that more attention should be paid to Gabor phases for face recognition purpose.

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References

1. Zhao W, Chellappa R, Phillips P, Rosenfeld A (2003) Face recognition: a literature survey. ACM Comput Surv 35(4):399–458
2. Phillips PJ, Grother P, Micheals RJ, Blackburn DM, Tabassi E, Bone JM (2003) Face recognition vendor test 2002 results. Evaluation Report
3. Phillips PJ, Syed HM, Rizvi A, Rauss PJ (2000) The FERET evaluation methodology for face-recognition algorithms. IEEE Trans PAMI 22(10):1090–1104
4. Shan S, Gao W, Chang Y, Cao B, Yang P (2004) Review the strength of Gabor features for recognition from the angle of its robustness to mis-alignment. In: Proceedings of the 18th international conference on pattern recognition (ICPR2004), vol 1, pp 338–341
5. Lades M, Vorbruggen J, Buhmann J, Lange J, Cvd Malsburg, Wurtz R, Konen W (1993) Distortion invariant object recognition in the dynamic link architecture. IEEE Trans Comput 42(3):300–311
6. Wiskott L, Fellous JN, Kruger N, Cvd Malsburg (1997) Face recogniton by elastic bunch graph matching. IEEE Trans PAMI 19(7):775–779
7. Liu C, Wechsler H (2002) Gabor feature based classification using the enhanced Fisher linear discriminant model for face recognition. IEEE Trans IP 11(4):467–476
8. Shan S, Yang P, Chen X, Gao W (2005) AdaBoost Gabor Fisher classifier for face recognition. In: Proceedings of international workshop on analysis and modeling of faces and gestures (AMFG 2005), LNCS 3723, pp 278–291
9. Shen L, Bai L (2006) A review on Gabor wavelets for face recognition. Pattern Anal Appl 9(10):273–292
10. Tao D, Li X, Wu X, Maybank SJ (2007) General tensor discriminant analysis and Gabor features for gait recognition. IEEE Trans PAMI 29(10):1700–1715
11. Li X, Maybank SJ, Yan S, Tao D, Xu D (2008) Gait components and their application to gender recognition. IEEE Trans SMC-C 38(2):145–155
12. Daugman J (2004) How iris recognition works? IEEE Trans CSVT 14(1):21–30
13. Zhang W, Shan S, Gao W, Chen X, Zhang H (2005) Local Gabor binary pattern histogram sequence (LGBPHS): a novel non-statistical model for face representation and recognition. In: Proceedings of the 10th IEEE international conference on computer vision (ICCV2005), pp 786–791
14. Ahonen T, Hadid A, Pietikäinen M (2004) Face recognition with local binary patterns. In: Proceeding of European conference on computer vision (ECCV2004), LNCS 3021, pp 469–481
15. Hadjidemetriou E, Grossberg MD, Nayar SK (2004) Multiresolution histograms and their use for recognition. IEEE Trans PAMI 26(7):831–847
16. Ojala T, Pietikäinen M, Harwood D (1996) A comparative study of texture measures with classification based on featured distribution. Pattern Recognit 29(1):51–59
17. Ojala T, Pietikäinen M, Mäenpää T (2002) Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans PAMI 24(7):971–987
18. Swain M, Ballard D (1991) Color indexing. Int J Comput Vis 7(1):11–32
19. Duda R, Hart P, Stork D (2001) Pattern classification, 2nd edn. Wiley-Interscience, New York

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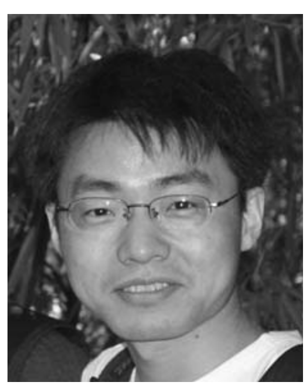

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