Fusing Magnitude and Phase Features for Robust Face Recognition

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Abstract. High accurate face recognition is of great importance for real-world applications such as identity authentication, watch list screening, and human-computer interaction. Despite tremendous progress made in the last decades, fully automatic face recognition systems are still far from the goal of surpassing the human vision system, especially in uncontrolled conditions. In this paper, we propose an approach for robust face recognition by fusing two complementary features: one is the Gabor magnitude of multiple scales and orientations and the other is Fourier phase encoded by Local Phase Quantization (LPQ). To further reduce the high dimensionality of both features, patch-wise Fisher Linear Discriminant Analysis is applied respectively and further combined by score-level fusion. In addition, multi-scale face models are exploited to make use of more information and improve the robustness of the proposed approach. Experimental results show that the proposed approach achieves 96.09%, 95.64% and 95.15% verification rates (when FAR=0.1%) on ROC1/2/3 of Face Recognition Grand Challenge (FRGC) version 2 Experiment 4, impressively surpassing the best known results, i.e. 93.91%, 93.55%, and 93.12%.

1 Introduction

Machine-based face recognition, as one of the most representative technologies of artificial intelligence, has attracted significant attention over the last decades in many domains such as entertainment[1] and surveillance[2]. Although numerous approaches have been proposed for face recognition and tremendous progress has been made, it is still difficult for machine to recognize human faces efficiently and accurately under uncontrolled conditions. The main challenges lie in the small interpersonal difference because of similar facial configurations, as well as the large intrapersonal variations caused by diverse extrinsic imaging factors such as pose, expression, aging, and lighting.

To achieve high accurate machine-based face recognition, numerous local descriptors have been proposed to extract effective information, such as Local

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Binary Patterns (LBP)[3] and its variants[4], Gabor wavelet transform based descriptors[5][6][7] and Local Phase Quantization (LPQ)[8]. As a single descriptor only encodes limited information of the given face, it is reasonable to combine different descriptors for more effective information. Recently, methods fusing diverse descriptors have received much attention, such as global and local descriptors[9], features extracted on multiple scales[10], different frequency bands[11], fusion of LBP and Gabor[12] and the enhanced Local Gabor Binary Patterns (LGBP)[6]. Intuitively, in fusing different features, the complementarity of the descriptors plays an important role, for example, global vs. local, single band vs. multiple bands. In recent years, the fusion of magnitude and phase in frequency domain has attracted a lot of attention[5][13]. In this work, we have made a new attempt to fuse Gabor magnitude and locally quantized Fourier phase. Specifically, we first extract the Gabor magnitude and Fourier phase features from a face image by using Gabor wavelet transform and Local Phase Quantization (LPQ), respectively. Then, to reduce the high dimensionality and increase the discriminative capability, patch-wise Fisher Linear Discriminant Analysis (FLDA)[14] is applied to extract the discriminative low dimensional features for classification. Finally, score level fusion is performed to calculate the final similarity. To better make use of multi-scale information, a multi-scale fusion of magnitude and phase is exploited to further improve the robustness.

To demonstrate the strength of the proposed approach, we test it on the large-scale face verification database, i.e., Face Recognition Grand Challenge (FRGC) version 2[15], following its standard Exp.4 evaluation protocol. The proposed approach impressively outperforms the best known counterparts, such as Local Binary Patterns (LBP) based methods[12], Gabor wavelet transform based methods[9][13], enhanced Fisher linear discriminant model[7], local descriptor fusion based methods[9][12][13][16] and color space based methods[17][18][19]. Experimental results show that the proposed approach achieves 96.09%, 95.64% and 95.15% verification rates (when FAR=0.1%) on ROC1/2/3 of FRGC v2.0 Exp.4, impressively surpassing the best known results, i.e. 93.91%, 93.55%, and 93.12%[16].

In summary, the main contribution of this paper lies in two aspects: 1) we show that the fusion of Gabor magnitude and locally quantized phase provides a complementary description for robust face recognition; 2) The proposed approach achieves the best known results in face verification under uncontrolled conditions. Specifically, we achieve about 96% verification rate on FRGC v2.0 Exp.4. In other words, the error rate is reduced by about 30% compared with the best known results.

The rest of this paper is organized as follows. Section 2 briefly describes the related work, e.g., Gabor wavelet transform and Local Phase Quantization (LPQ). The proposed approach is detailed in Section 3. Experimental evaluation of the proposed approach is presented in Section 4. Finally, we conclude the work in Section 5.

2 Background

2.1 Gabor Wavelet Transform

Gabor wavelet transform is similar to Fourier transform in many ways but has a limited spatial scope. Local face descriptors based on Gabor wavelet have been proved to be one of the most successful face representation methods in recent years. The Gabor wavelet representation of an image is defined as the convolution of the image with Gabor kernels[7], given by

$$G_{u,v}(z) = I(z) * \varphi_{u,v}(z). \tag{1}$$

Here, $I(z)$ denotes the input image, and $*$ denotes the convolution operator. z denotes the pixel coordinate, i.e., $z = (x, y)$, and $\varphi_{u,v}(\cdot)$ is the Gabor kernel with orientation u and scale v, which is defined as follows:

$$\varphi_{u,v}(z) = \frac{\|k_{u,v}\|^2}{\sigma^2} e^{(-\|k_{u,v}\|^2\|z\|^2/2\sigma^2)}[e^{ik_{u,v}z} - e^{-\sigma^2/2}], \tag{2}$$

where $\|\cdot\|$ denotes the norm operator, and the wave vector $k_{u,v}$ is defined as follows:

$$k_{u,v} = k_v e^{i\phi_u}, \tag{3}$$

where $k_v = k_{max}/f^v$ and $\phi_u = \pi u/8$; k_{max} is the maximum frequency, and f is the spacing between kernels in the frequency domain. For each Gabor kernel, at every pixel of the image, a complex number can be generated which contains two Gabor parts (real part $\mathrm{Re}_{u,v}(z)$ and imaginary part $\mathrm{Im}_{u,v}(z)$). Based on these two parts, magnitude information $M_{u,v}(z)$ can be computed by

$$M_{u,v}(z) = \sqrt{\mathrm{Re}^2_{u,v}(z) + \mathrm{Im}^2_{u,v}(z)}. \tag{4}$$

2.2 Local Phase Quantization

Local Phase Quantization (LPQ) utilizes the phase information locally extracted using the Short Term Fourier Transform (STFT) computed over a square $M \times M$ neighborhood N_x at each pixel position x of the image $f(x)$[8] defined by

$$F(u, x) = \sum_{y \in \mathrm{N}_x} f(x - y) e^{-j2\pi u^T y} = w_u^T f_x, \tag{5}$$

where f_x is a vector containing all the M^2 gray-scale values from N_x, w_u is the basis vector of the STFT at frequency u. Only four complex coefficients are selected in LPQ, corresponding to 2-D frequencies $u_1 = [a, 0]^T$, $u_2 = [0, a]^T$, $u_3 = [a, a]^T$ and $u_4 = [a, -a]^T$. Let

$$F_x^c = [F(u_1, x), F(u_2, x), F(u_3, x), F(u_4, x)], \tag{6}$$

and

$$F_x = [\mathrm{Re}\{F_x^c\}, \mathrm{Im}\{F_x^c\}]^T, \tag{7}$$

where Re{·} and Im{·} are real and imaginary parts of a complex number, respectively. So, the corresponding $8 \times M^2$ transformation matrix is

$$W = [\mathrm{Re}\{w_{u_1}, w_{u_2}, w_{u_3}, w_{u_4}\}, \mathrm{Im}\{w_{u_1}, w_{u_2}, w_{u_3}, w_{u_4}\}]^T, \tag{8}$$

so that

$$F_x = W f_x. \tag{9}$$

Assuming that $f(x)$ is a result of a first-order Markov process, where the correlation coefficient between adjacent pixel gray-scale values and the variance of each sample are ρ and σ^2 (assuming $\sigma^2 = 1$ without a loss of generality), respectively. As a result, the covariance between positions x_i and x_j can be expressed by

$$\sigma_{ij} = \rho^{\|x_i - x_j\|_{L_2}}. \tag{10}$$

Hence, the covariance matrix of all M samples in N_x can be expressed by

$$C = \begin{bmatrix} 1 & \sigma_{12} & \cdots & \sigma_{1M} \\ \sigma_{21} & 1 & \cdots & \sigma_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{M1} & \sigma_{M2} & \cdots & 1 \end{bmatrix}. \tag{11}$$

As a result, the covariance matrix of F_x can be obtained from

$$D = WCW^T. \tag{12}$$

We can easily notice that the coefficients are correlating, as D is not a diagonal matrix when $\rho > 0$. The coefficients should be de-correlated using a whitening transform before quantization, because it can be shown that if the samples to be quantized are statistically independent, information can be maximally preserved in scalar quantization. Whitening transform can be expressed by

$$G_x = V^T F_x, \tag{13}$$

where V is an orthonormal matrix derived from the singular value decomposition (SVD) of matrix D. G_x is computed for every image position, and the resulting vectors are quantized by a simple scalar quantizer

$$q_j = \begin{cases} 1, & \text{if } g_j \geq 0 \\ 0, & \text{otherwise} \end{cases}, \tag{14}$$

where g_j is the jth component of G_x. Eventually, the quantized coefficients can be represented as integer values from 0 to 255 using binary coding

$$b = \sum_{j=1}^{8} q_j 2^{j-1}. \tag{15}$$

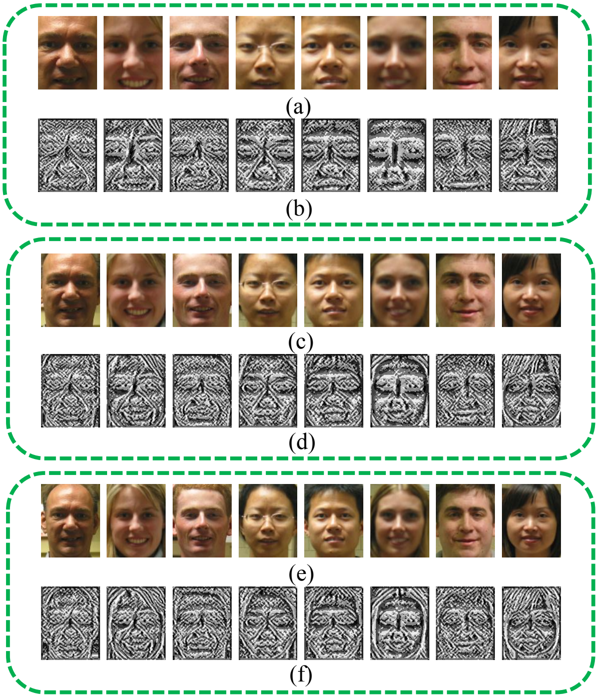

Fig. 1. Face images used in the (a) internal, (c) transitional and (e) external models. The corresponding LPQ features are shown in (b), (d) and (f).

3 The Proposed Approach

3.1 Fusion of Magnitude and Phase Features

Since the pioneering work of Lades et al.[20], Gabor wavelets which have been widely used in face recognition, possibly due to the fact that they can well approximate the receptive fields of simple cells in the primary visual cortex of human vision system. In practice, Gabor wavelets can take a variety of different forms with different scales and orientations. Gabor wavelet with a certain orientation responds to edges and bars along this direction, and a certain scale Gabor wavelet extracts the information within the corresponding frequency band. As a result, Gabor wavelets can be used to extract abundant local structure details in some important facial areas which are very crucial for efficient face representation. Here we utilize the magnitude part acquired from the Gabor wavelet transform. In the field of local descriptor fusion, the primary factor that we should take into consideration is the complementarity of the local descriptors to be fused. In frequency domain, magnitude information can capture the facial structure and phase information can give a detailed description of facial texture. In this work, we use Local Phase Quantization (LPQ) to locally encode the

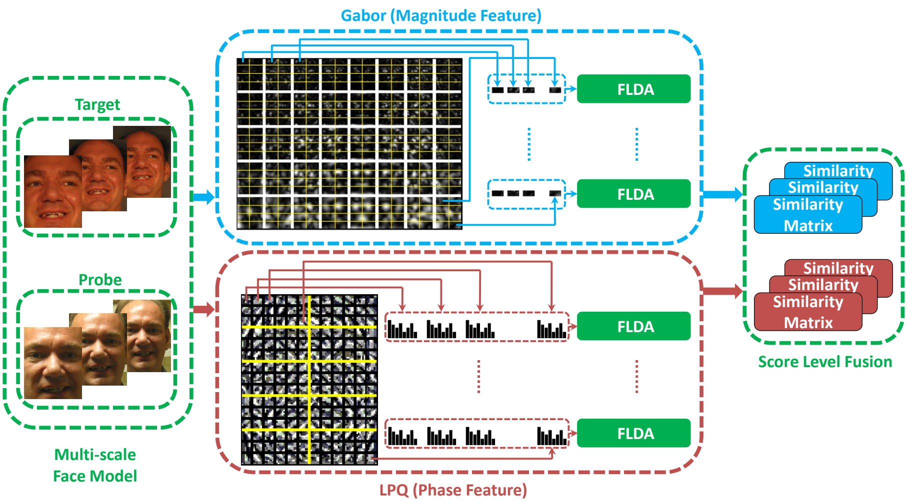

Fig. 2. The proposed approach which fuses magnitude and phase features. The Gabor magnitude extraction part is encircled by light blue dotted box and the LPQ phase extraction part is encircled by dark red dotted box.

Fourier phase information. LPQ is a descriptor first applied to texture identification because it is highly insensitive to image blurring caused by motion, out of focus or atmospheric turbulence[8]. This descriptor utilizes quantized phase of the 2-D Discrete Fourier Transform (DFT), and the phase information of four low frequency coefficients are quantized uniformly into an eight-dimensional subspace. The resulting decimal code words create a histogram which is finally used as the feature in texture identification. Fig. 1 shows some examples of LPQ feature.

The locality information will not be completely utilized, if all the features are concatenated to a long single vector. To overcome this potential weakness, features in our approach are spatially grouped into a number of feature vectors (patch-based representation), by doing this more locality information can be preserved. Each patch corresponds to a local area of the image and is of relatively low dimensionality which means less computing price. In addition, compared to holistic representation, this patch-based method is much more robust to illumination variation. The reason is that the illumination variation within the whole image is much greater than that within each patch.

Fig. 2 shows our approach, where the Gabor magnitude extraction part is encircled by light blue dotted box and the LPQ phase extraction part is encircled by dark red dotted box. Each face model will generate two similarity matrices after feeding into our approach, one is for Gabor magnitude part and one is for LPQ phase part. Finally, fusion is conducted at the score level by summating the six matrices.

3.2 Multi-scale Face Model

Sinha et al.[21] pointed out that the human vision system's processing to judge one's identity is better characterized as "head recognition" rather than "face recognition". Apparently, it is difficult for some people to determinate whether two faces are of the same subject based only on the internal images as shown in row (a) of Fig. 1. However, one may more easily recognize a face if given the external image in row (e) of Fig. 1. Behind this interesting phenomenon, the rationale is that humans tend to rely on the contextual information to recognize faces, such as hair style, head contour and jaw, especially when intrinsic information is degraded[16]. Thus, it is smart to add a multi-scale face model which contains not only intrinsic but also holistic contextual information. With above analysis, in the proposed approach, three normal face templates of different scales (i.e., internal face, transitional face and external face) are taken into account to best imitate human vision system. As can be seen, the internal face model contains only the internal facial organs, such as eyes, mouth, nose and eyebrows which are affected only by the factors related to identity. On the contrary, the external face model is portrait-like and contains some external facial elements such as jaw, head contour and hair. The transitional face image can be regarded as the transition state from internal face model to external face model.

4 Experiment and Analysis

4.1 The FRGC Version 2 Experiment 4

Face Recognition Grand Challenge (FRGC) is a large-scale face recognition evaluation system sponsored by the United States government and collected at the University of Notre Dame. This face database is designed to achieve the goal that reducing the error rate of face recognition systems by an order of magnitude. With above goal, it presents six challenging experiments along with data corpus of 50,000 recordings divided into training and validation partitions to researchers. The data consists of high resolution still images taken under controlled and uncontrolled conditions. The controlled images taken in a studio setting (two or three studio lights) are full frontal facial images with two facial expressions (neutral and smiling). The uncontrolled images were taken in varying lighting conditions; e.g., atria, hallways, or outdoors. Each set of uncontrolled images also contains two expressions, neutral and smiling. As recognizing faces under uncontrolled conditions which is considered the security requirement for real-world biometric recognition has numerous applications and is one of the most challenging problems in the field of face recognition, we choose Experiment 4 to evaluate our approach. In Experiment 4, training set consists of 12,776 images of 222 subjects, with 6,388 controlled still images and 6,388 uncontrolled still images. The target set consists of 16,028 controlled still images, and the query set consists of 8,014 uncontrolled still images.

4.2 Technical Details

The input internal, transitional and external face images we use in our approach are first normalized to 120 × 96 pixels image with the centers of the eyes located at (20, 47) and (75, 47), (26, 47) and (69, 47) and (29, 51) and (66, 51), respectively. Then, we use PP[22] which has been proven a robust illumination normalization method to further normalize the input images.

In the Gabor magnitude feature extraction process, 40 Gabor wavelets with 5 scales and 8 orientations are utilized, where the Gabor kernel's size, the maximum frequency k_{max}, the spacing between kernels in the frequency domain f and the parameter σ are set to 31 × 31, 1.0, $\sqrt{2}$ and 2.0, respectively. 40 Gabor magnitude images are generated after the convolution with the 40 Gabor kernels, after that we use a 4 × 4 down sampling to the 40 Gabor magnitude images to reduce the huge dimensionality of the original feature. As mentioned above, our approach is based on patches, so we divide every down sampled image into ten patches (5 rows by 2 columns) and concatenate the features of the same patch into a single vector which acts as a classifier.

In the LPQ phase feature extraction process, the correlation coefficient ρ, the sliding window's size and the frequency parameter a are set to 0.9, 7 × 7 and 1/7, respectively. In this process, we extract LPQ histogram on every 8 × 8 pixels block, and then organize the histograms to form an 18-patch structure (6 rows by 3 columns) as shown in Fig. 2.

To further reduce the patches' dimensionality, Fisher Linear Discriminative Analysis (FLDA) is utilized on every patch in our approach. We set the PCA dimensionality 600 and 500 in the Gabor part and LPQ part, respectively. The LDA dimensionality is set to 221 that one less than subject amount (222 subjects) of the training set in both parts. After that, we fused the scores (cosine) using the simple sum rule with equal weights for each feature and each scale. Note that the score normalization on similarity matrices before the fusion is helpful, because commensurability of them can be guaranteed by doing this.

4.3 Results and Discussions

The results of the FRGC version 2.0 Exp.4 which measured by a standard procedure allow for the fair comparison between the proposed system and other current face recognition systems. Table 1 summarizes the performance of sixteen state-of-the-art methods that have been proposed since FRGC 2005. Compared to the other methods, ours (96.09% @ FAR = 0.1%) tremendously boosts the accuracy of the face verification.

Table 1 also shows the critical role of fusion of local descriptors in uncontrolled face verification: no single descriptor based method can surpass the verification rate of 85%. For this reason, we are going to put emphasis on the comparison with fusion based methods. The result of comparing our approach with Xie et al.[13]'s which fuses magnitude and phase features both from Gabor wavelet transform shows that, the complementarity between Gabor magnitude and Gabor phase is much weaker than that between Gabor magnitude and LPQ based phase. Fig. 3

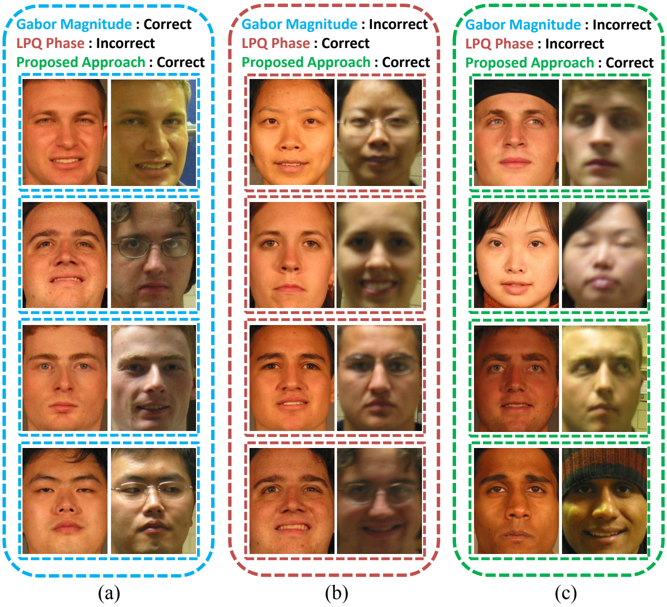

Fig. 3. Complementarity between Gabor magnitude feature and LPQ phase feature. (a) Pairs which verified correctly by Gabor magnitude feature while incorrectly verified by LPQ phase feature. (b) Pairs which verified correctly by LPQ phase feature while incorrectly verified by Gabor magnitude feature. Notice that all the pairs in (a) and (b) are correctly verified by the proposed approach. (c) Pairs that neither Gabor magnitude nor LPQ phase feature works on them but verified correctly by the proposed approach.

presents some examples that illustrate the complementarity of Gabor magnitude and LPQ phase features. Only matched pairs (two faces in the pair are of the same subject) of ROC I are used here. Column (a) shows pairs which verified correctly by Gabor magnitude feature while incorrectly verified by LPQ phase feature, on the contrary, column (b) shows the opposite situation. Notice that all the pairs in column (a) and (b) are correctly verified by the proposed approach. Column (c) shows pairs that neither Gabor magnitude nor LPQ phase feature works on them but verified correctly by the proposed approach. As can be seen, Gabor magnitude feature captures the structure information of the face, and it is robust to slight pose variation. LPQ phase feature is more robust to blurred image by efficiently encoding the facial texture.

The proposed approach which fuses magnitude and phase features can cope well with uncontrolled condition including pose and illumination variation, occlusion and blur. Multi-scale face model as a best imitation of human being's visual system also play an important role in face verification, we can notice that the highest two results (ours and Deng et al.'s[16]) both utilize multi-scale face model. We mainly attribute our significant result to the fusion of complementary three face scales and two features. As shown in Table 1, the verification rates (VR) on ROC1 of Gabor feature on three scales are 92.17%, 92.10% and

Table 1. Comparative verification rates at 0.1% FAR of state-of-the-art face recognition systems for Face Recognition Grand Challenge version 2 Experiment 4.

Method	Ref.	Feature	ROC I	ROC II	ROC III
BEE Baseline	[15]	Pixel	0.1336	0.1267	0.1186
KCFA	[23]	Pixel	N/A	N/A	0.57
R-WWC	[24]	Pixel	0.35	0.35	0.35
Extended GCID	[25]	Pixel	0.7890	0.7866	0.7826
MFM-HFF	[11]	Fourier	0.7570	0.7506	0.7433
DIF	[26]	Gabor	0.72	0.74	0.76
YQCr	[17]	YQCr	0.6447	0.6489	0.6521
HVDA	[18]	YQCr	0.7865	0.7850	0.7824
LEC	[9]	Gabor	N/A	N/A	0.83
KDCV	[12]	LBP	N/A	N/A	0.735
LGBP+LGXP	[13]	LGBP+LGXP	0.836	0.843	0.849
HEC	[9]	Gabor+Fourier	N/A	N/A	0.89
KDCV	[12]	Gabor+LBP	N/A	N/A	0.836
PSMLPQ+PSMLBP+KDA	[27]	LBP+LPQ	0.8292	0.8434	0.8572
Hybrid RCrQ	[19]	Gabor+MLBP+DCT	N/A	N/A	0.924
RTF+RCF	[16]	RTF+RCF	0.9391	0.9355	0.9312
Gabor(internal)	ours	Gabor	0.9217	0.9199	0.9178
Gabor(transitional)	ours	Gabor	0.9210	0.9140	0.9060
Gabor(external)	ours	Gabor	0.9243	0.9161	0.9068
LPQ(internal)	ours	LPQ	0.8244	0.8211	0.8171
LPQ(transitional)	ours	LPQ	0.8448	0.8328	0.8194
LPQ(external)	ours	LPQ	0.8380	0.8198	0.7989
Fused System	ours	Gabor + LPQ	**0.9609**	**0.9564**	**0.9515**

92.43%, respectively (while their fusion result is 94.56%). Similarly, the VRs of LPQ on three scales are 82.44%, 84.48% and 83.80% respectively (while the result is impressively improved to 92.06% after fusion). When all the scales of both features are fused together, the VR is further improved to 96.10% (from 94.56% and 92.06%). These results reveal the complementarity of both different scales and different features. We also performe face identification on the same dataset of FRGC v2.0 Exp.4, by using its target set as gallery and query set as probe, and we achieve an identification rate of 99.70%. It is important to note that our performance surpasses all the color space based methods, although only gray-scale images are used in our method.

As multi-scale model is applied, we list the time cost in the following text. The most time-consuming step in the proposed approach is feature extraction. We assesse the computation cost of our feature extraction on a PC with Intel Core i5 3.1GHz processor. Without any special optimization or multi-core parallel, the time for one scale is 40ms for Gabor and 12ms for LPQ. Thus, the time required for 3 scales is 156ms. If all the features for the gallery set are computed offline, our system is able to perform identification with about 6 probes per second.

5 Conclusion

In this paper, by fusing complementary Gabor magnitude and locally quantized Fourier phase features, we achieved near perfect recognition ($\approx 96\%$) on FRGC v2.0 Exp.4 at FAR=0.1%. From the good results, we can draw the following conclusions: 1) Gabor magnitude provides discriminative information for face recognition; 2) Locally quantized Fourier phase information is very robust to degraded (especially blurred) face images; 3) Gabor magnitude and Fourier phase are very complementary in terms of distinguishing faces.

Although impressive results are achieved on FRGC v2.0, we need more efforts to further study its applicability to other face recognition scenarios. It is also desirable to try other fusion methods.

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References

1. Oda, R.: Biased face recognition in the prisoner's dilemma game. Evolution and Human Behavior 18, 309–315 (1997)
2. Burton, A., Wilson, S., Cowan, M., Bruce, V.: Face recognition in poor-quality video: Evidence from security surveillance. Psychological Science 10, 243–248 (1999)
3. Ahonen, T., Hadid, A., Pietikäinen, M.: Face Recognition with Local Binary Patterns. In: Pajdla, T., Matas, J(G.) (eds.) ECCV 2004. LNCS, vol. 3021, pp. 469–481. Springer, Heidelberg (2004)
4. Ojala, T., Pietikäinen, M., Maenpaa, T.: Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans. on PAMI 24, 971–987 (2002)
5. Huang, L., Shimizu, A., Kobatake, H.: Robust face detection using gabor filter features. Pattern Recognition Letters 26, 1641–1649 (2005)
6. Zhang, W., Shan, S., Gao, W., Chen, X., Zhang, H.: Local gabor binary pattern histogram sequence (lgbphs): A novel non-statistical model for face representation and recognition. In: ICCV, vol. 1, pp. 786–791. IEEE (2005)
7. Liu, C., Wechsler, H.: Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition. IEEE Trans. on Image Processing 11, 467–476 (2002)
8. Ojansivu, V., Heikkilä, J.: Blur Insensitive Texture Classification Using Local Phase Quantization. In: Elmoataz, A., Lezoray, O., Nouboud, F., Mammass, D. (eds.) ICISP 2008 2008. LNCS, vol. 5099, pp. 236–243. Springer, Heidelberg (2008)
9. Su, Y., Shan, S., Chen, X., Gao, W.: Hierarchical ensemble of global and local classifiers for face recognition. IEEE Trans. on Image Processing 18, 1885–1896 (2009)

10. Lin, D., Tang, X.: Recognize high resolution faces: From macrocosm to microcosm. In: CVPR, vol. 2, pp. 1355–1362. IEEE (2006)
11. Hwang, W., Park, G., Lee, J., Kee, S.: Multiple face model of hybrid fourier feature for large face image set. In: CVPR, vol. 2, pp. 1574–1581. IEEE (2006)
12. Tan, X., Triggs, B.: Fusing Gabor and LBP Feature Sets for Kernel-Based Face Recognition. In: Zhou, S.K., Zhao, W., Tang, X., Gong, S. (eds.) AMFG 2007. LNCS, vol. 4778, pp. 235–249. Springer, Heidelberg (2007)
13. Xie, S., Shan, S., Chen, X., Chen, J.: Fusing local patterns of gabor magnitude and phase for face recognition. IEEE Trans. on Image Processing 19, 1349–1361 (2010)
14. Shan, S., Zhang, W., Su, Y., Chen, X., Gao, W.: Ensemble of piecewise fda based on spatial histograms of local (gabor) binary patterns for face recognition. In: ICPR, vol. 4, pp. 606–609. IEEE (2006)
15. Phillips, P., Flynn, P., Scruggs, T., Bowyer, K., Chang, J., Hoffman, K., Marques, J., Min, J., Worek, W.: Overview of the face recognition grand challenge. In: CVPR, vol. 1, pp. 947–954. IEEE (2005)
16. Deng, W., Hu, J., Guo, J., Cai, W., Feng, D.: Emulating biological strategies for uncontrolled face recognition. Pattern Recognition 43, 2210–2223 (2010)
17. Shih, P., Liu, C.: Improving the face recognition grand challenge baseline performance using color configurations across color spaces. In: ICIP, pp. 1001–1004. IEEE (2006)
18. Yang, J., Liu, C.: Horizontal and vertical 2dpca-based discriminant analysis for face verification on a large-scale database. IEEE Trans. on Information Forensics and Security 2, 781–792 (2007)
19. Liu, Z., Liu, C.: Robust Face Recognition Using Color Information. In: Tistarelli, M., Nixon, M.S. (eds.) ICB 2009. LNCS, vol. 5558, pp. 122–131. Springer, Heidelberg (2009)
20. Lades, M., Vorbruggen, J., Buhmann, J., Lange, J., von der Malsburg, C., Wurtz, R., Konen, W.: Distortion invariant object recognition in the dynamic link architecture. IEEE Trans. on Computers 42, 300–311 (1993)
21. Sinha, P., Poggio, T.: I think i know that face. Nature 384, 404–404 (1996)
22. Tan, X., Triggs, B.: Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions. In: Zhou, S.K., Zhao, W., Tang, X., Gong, S. (eds.) AMFG 2007. LNCS, vol. 4778, pp. 168–182. Springer, Heidelberg (2007)
23. Kumar, B., Savvides, M., Xie, C.: Correlation pattern recognition for face recognition. Proceedings of the IEEE 94, 1963–1976 (2006)
24. Liu, C.: The bayes decision rule induced similarity measures. IEEE Trans. on PAMI 29, 1086–1090 (2007)
25. Yang, J., Liu, C.: Color image discriminant models and algorithms for face recognition. IEEE Trans. on Neural Networks 19, 2088–2098 (2008)
26. Liu, C.: Capitalize on dimensionality increasing techniques for improving face recognition grand challenge performance. IEEE Trans. on PAMI 28, 725–737 (2006)
27. Chan, C.-H., Kittler, J., Tahir, M.A.: Kernel Fusion of Multiple Histogram Descriptors for Robust Face Recognition. In: Hancock, E.R., Wilson, R.C., Windeatt, T., Ulusoy, I., Escolano, F. (eds.) SSPR&SPR 2010. LNCS, vol. 6218, pp. 718–727. Springer, Heidelberg (2010)