DISGUISED FACE RECOGNITION VIA LOCAL PHASE QUANTIZATION PLUS GEOMETRY COVERAGE

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ABSTRACT

Disguised face recognition (FR) is considered as one of the difficult and important problems in FR field. Rather than disguised modeling, a disguised face recognition algorithm based on local phase quantization (LPQ) feature and geometry coverage is presented in this paper. LPQ method is applied to extract the phase statistics feature which is robust to the disguised mode, and hyper sausage neuron based on biomimetic pattern recognition (BPR) theory is adopted to construct high-dimensional geometry coverage of different classes, which makes full use of continuous characteristics of different class face features while avoids the interruption of the disguised mode. Experiments on AR face database and disguised face database established by police face combination software show that, compared with the state-of-the-art method, the proposed recognition algorithm can achieve high recognition results under disguised conditions.

Index Terms— Disguised face recognition, Local phase quantization, Biomimetic pattern, Geometry coverage

1. INTRODUCTION

Face recognition is one of the most important research topic in pattern recognition and artificial intelligence. Due to difficulties of overcoming illumination, resolution, expression, pose, age and disguised variations, it has remained a hot research direction [1]. In recent years, many algorithms for robust illumination, pose and expression variations has been proposed [2, 3], but for the disguised, glasses, mustache, ages variations, it still remains unsolved [4–7]. For national security recognition circumstances, such as the recognition of criminals or terrorists at large, deliberate face camouflages on mustache, sunglasses, hat, eyebrow, lip, age and etc. are often done to hide their genuine identity. These face images are named disguised face images, as shown in Fig. 1, and the problem of recognizing them is very challenging.

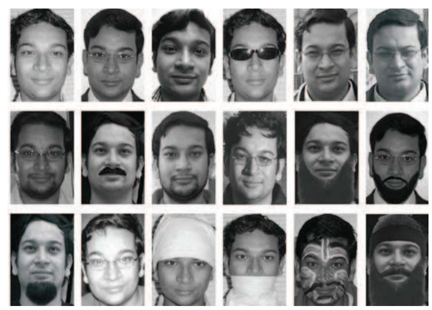

Fig. 1. Disguised face images from the same person

Ramanathan et al [7] utilized the feature space of left half face and right half one to seek for relative optimal side for feature projection, but performance for disguised face recognition still needs to be improved. Singh et al [8] proposed a dynamic neural network framework and 2D Log Gabor transform to extract phase features, then split these into multi-frames for Hamming matching, and achieved a relatively good results, but these results are not satisfying yet.

Different from the methods above, in this paper, we try to solve the disguised face recognition problem from the aspects of more effective features and geometry coverage of the same person in high-dimensional space. In feature extraction process, local phase quantization (LPQ) [9] is extracted for effective and stable feature for recognizing faces in disguised condition. While for recognition algorithm, geometry coverage method based on biomimetic pattern recognition theory [10], which focuses more on the view of "recognization", but not "classification", is adopted to seeking an appropriate geometry coverage in high-dimensional space by the intrinsic continuous characteristic of samples from the same person, to identify the disguised faces.

The rest of the paper is organized as follows. In Section 2, the disguised face recognition approach is presented in the aspects of local phase quantization and geometry coverage respectively. Section 3 demonstrates the performance of the

National Natural Science Foundation under Grand (No.61072127); and Natural Science Foundation of Guangdong Province, P.R.C. under Grand (No.10152902001000002, No.S2011040004211, No.S2011010001085 and No.07010869); and Foundation for Distinguished Young Talents in Higher Education of Guangdong, China Under Grand No.2012LYM_0127.

proposed method on two disguised face databases. Section 4 concludes the paper and gives perspective ideas for future work.

2. PROPOSED APPROACH

In our disguised face recognition approach, LPQ feature is extracted for effective and stable features. Then, geometry coverage model based on BPR is performed for robust disguised face recognition.

2.1. Feature Extraction based on LPQ

LPQ descriptor which proposed by Ojansivu [9] has gained reputation these years for its outstanding performance in image texture analysis. In LPQ method, fourier phase spectrum is utilized to extract robust features. Firstly, Short time Fourier Transform (STFT) is computed over a $M \times M$ local rectangular window N_x at each pixel x of the image $f(x)$ in LPQ, that is

$$F(u,x) = \sum_{y \in N_x} f(x-y) e^{-j2\pi u^T y} = w_u^T f_x \tag{1}$$

where w_u is the basis vector of the STFT at frequency u, and f_x is another vector containing all M^2 image pixels from N_x.

Only 2-D frequencies $u_1 = [a,0]^T, u_2 = [0,a]^T, u_3 = [a,a]^T, u_4 = [a,-a]^T$ are considered in LPQ. Let

$$F_x^c = [F(u_1,x), F(u_2,x), F(u_3,x), F(u_4,x)] \tag{2}$$

$$F_u = [\mathrm{Re}(F_x^c), \mathrm{Im}(F_x^c)]^T \tag{3}$$

where $\mathrm{Re}(\cdot)$ and $\mathrm{Im}(\cdot)$ return real and imaginary parts of a complex number respectively. The corresponding 8 by M^2 transformation matrix is

$$W = [\mathrm{Re}(w_{u_1}, w_{u_2}, w_{u_3}, w_{u_4}), \mathrm{Im}(w_{u_1}, w_{u_2}, w_{u_3}, w_{u_4})]^T \tag{4}$$

so that

$$F_x = W f_x \tag{5}$$

For robust phase feature, F_x can be decorrelated via the whitening transformation [11] and singular value decomposition (SVD), then the final feature G_x can be obtained. where g_j is the j_{th} component of G_x. The quantized coefficients are represented as integer values between 0-255 using binary coding

$$b = \sum_{j=1}^{8} q_j 2^{j-1} \tag{6}$$

Finally, a histogram of these integer values from all pixels is composed and used as a 256-dimensional feature vector. Five LPQ images of a disguised face are calculated under different scales in which LPQ window size takes different value respectively, as shown in Fig. 2. To achieve the best performance results, LPQ local window size is a key parameter in feature extraction.

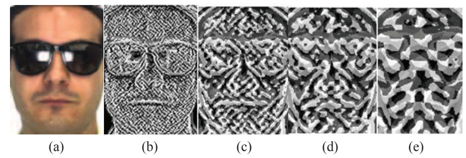

Fig. 2. Disguised face image (a) and the corresponding quantized phase features (b-e) obtained by different LPQ local window scale

2.2. Geometry coverage via Biomimetic Pattern Recognition

Biomimetic Pattern Recognition (BPR) [10, 12] was first proposed as a new pattern recognition model by academician Wang Shoujue. Different from the "division" concept of traditional pattern recognition, BPR emphasizes the view point of the function and mathematical model of pattern recognition on the concept of "cognition", which is much closer to the function of human being. Moreover, BPR aims at the optimal coverage of the samples of the same type, while traditional pattern recognition aims at the optimal classifications of different types of the samples in the feature space. Particularly, the construction of the subspace of a certain type of samples depends on analyzing the relations between the specific types of samples and utilizing the methods of "coverage of objects with complicated geometrical forms in the high-dimensional space".

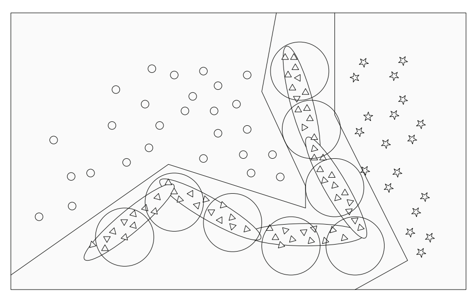

Fig. 3. Schematic diagram of the difference of BP, RBF, and BPR.

In Fig. 3, the triangles represent the samples to be recognized, and the small circles and crisscrosses represent the samples of the other types. Then the broken lines represent the division methods of Pattern Recognition based on BP network, the large circles represent those of RBF network (these methods are equal to the ones based on template matching), and long ellipses represent the "recognition" methods of BPR.

An important and essential focus of attention in BPR is the principle of homology-continuity (PHC):

In the feature space R^n, set A is assumed to include all the samples which belong to class A. And if there are any two samples x and y in set A, there must be a set B for any $\varepsilon > 0$:

$$B = \{x_1, x_2, \cdots, x_n \mid x_1 = x, x_n = y, n \subset N, 0 < \rho(x_m, x_{m+1}) < \varepsilon, \varepsilon > 0, n-1 \geq m \geq 1, m \subset N\} \tag{7}$$

where $B \subset A$, $\rho(x_m, x_{m+1})$ is the distance between x_m and x_{m+1}.

According to the principle above, the differences between any two samples from the same class are continuous. In other words, there exists a gradual process for one class including all the possible samples in which one sample may be slightly different from the other.

3. EXPERIMENTAL RESULTS

In order to evaluate the effectiveness of proposed recognition approach, two databases are adopted here. The first one is AR face database [13]which is substantially more challenging among the public released databases. AR face database consists of over 4,000 frontal images for 126 individuals. For each individual, 26 images were taken in two separate sessions, one session samples of a person are shown in Fig. 4. These images include more facial variations, such as illumination change, expressions, facial sunglasses occluded disguise and scarf disguise. A subset of the data set consisting of 50 male subjects and 50 female subjects is chosen for the experiment.

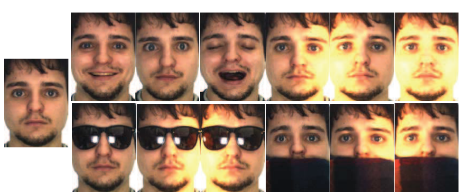

Fig. 4. Face images from the same person in AR face Database.

The other database is specially designed by us for performance evaluation by the IQ Biometric Faces Software [14] using the same method as reference [8]. The software is adopted by worldwide police organization including US CIA and FBI, and helps arresting criminals escaped for over five years successfully. There are lots of disguised modes which have representativeness and authenticity in certain extend. The disguised face database designed (named DS database in the following) consists of 100 individuals, each individual has 16

Fig. 5. Face images from the same person in disguised face database

face images. One session samples of a person are shown in Fig. 5, in which there are 1 frontal face image and 15 disguised images. The disguised mode includes variations of sunglasses, mustache, hats, eyebrow, smile and etc. The processed face image is with the resolution of 150×116.

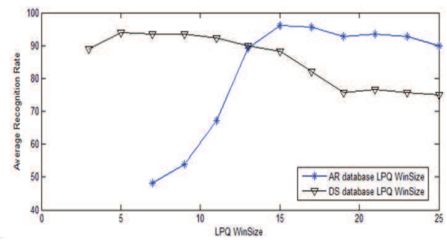

Fig. 6. Average Recognition Rate of the Proposed Algorithm vs LPQ WinSize in AR and DS face Database

Table 1. Performance of genuine users and imposters on AR face database via proposed algorithm under varying hyper sausage neuron radius value k , while LPQ WinSize is selected as optimal value 15.

Results of Genuine Users				Results of Imposters			All Users
k	TRR	FRR	FRR*	k	TRR*	FAR*	TRR
370	95.10%	0.33%	4.57%	370	99.89%	0.11%	99.89%
380	95.90%	0.44%	3.66%	380	99.66%	0.34%	99.66%
382	96.30%	0.44%	3.26%	382	98.72%	1.28%	98.72%
385	**96.80%**	**0.54%**	**2.65%**	**385**	**97.94%**	**2.06%**	**97.94%**
390	96.94%	0.95%	2.11%	390	96.35%	3.65%	96.35%
400	97.04%	1.22%	1.73%	400	92.94%	6.75%	92.94%
410	97.21%	1.22%	1.56%	410	81.35%	18.65%	81.35%
420	97.69%	1.77%	0.54%	420	69.52%	30.48%	69.52%

We will demonstrate the robustness of the disguised face recognition algorithm via both of the genuine users and imposters in these two databases. Performance comparison of other state-of-the-art methods is also presented. Here,70 subjects are randomly selected as genuine users; the left 30 subjects are used as the imposters. Half images of each genuine subjects are randomly selected for training, and the other half are for testing. For reducing the randomness of sample relying, experiments presented here takes the average results from 100 independent experiments. The proposed algorithm is implemented on an Intel Dual Core 2.60 GHz machine and applied with Matlab 2010b image processing toolbox.

There are two key parameters in the proposed algorithm, which is the value of local window size (WinSize) and the value of hyper sausage neural radius (k). We first fix the value of k as 385 which is initially selected via multiple experiments, and consider the impact of WinSize selection here. Various WinSize value will influence the final true recognition rate and true rejection rate here, and we take the average recognition rate as the average of the above true recognition and rejection rates to evaluate the performance. Experimental results show that for AR face database, the best average recognition rate is 97.94% while WinSize takes the value of 15; for DS database, the best average recognition rate is 93.94% while WinSize takes the value of 5, as shown in Fig 6.

Table 2. Performance of genuine users and imposters on DS face database via proposed algorithm under varying hyper sausage neuron radius value k , while LPQ WinSize is selected as optimal value 5.

Results of Genuine Users				Results of Imposters			All Users
k	TRR	FRR	FRR*	k	TRR*	FAR*	TRR
330	88.86%	11.14%	0.00%	330	99.44%	0.56%	94.15%
335	89.71%	10.29%	0.00%	335	100.00%	0.00%	94.86%
340	90.93%	9.07%	0.00%	340	100.00%	0.00%	95.47%
345	91.08%	8.92%	0.00%	345	99.44%	0.56%	95.26%
350	**92.43%**	**7.57%**	**0.00%**	**350**	**98.89%**	**1.11%**	**95.66%**
355	91.48%	8.52%	0.00%	355	99.44%	0.56%	95.46%
360	91.05%	8.95%	0.00%	360	98.89%	1.11%	94.97%
365	92.90%	7.10%	0.00%	365	97.78%	2.22%	95.34%

Since hyper sausage neural model is adopted to construct high-dimensional space geometry coverage in the proposed algorithm, the hyper sausage neural radius value *k* is a crucial parameter here. The following experiments will evaluate the performance and relationship of true recognition rate and true rejection rate under varying *k* value while LPQ WinSize takes the above optimal value. For genuine users, true recognition rate (TRR), false recognition rate (FRR), false rejection rate (FRR*) are evaluated; while for imposters, true rejection rate (TRR*) and false acceptance rate (FAR*) are evaluated. Results are listed in Table 1 and Table 2. From Table 1, we can see that with the increasing of BPR threshold value *k* from 370 to 420, the true rejection rate in AR face database declined from 99.89% to 69.52%, while the true recognition rate rose from 95.10% to 97.69%. The geometry coverage of hyperlinks in the feature space is small when BPR threshold *k* is 370. Thus a good result of true rejection rate has been obtained. But with the increasing of BPR threshold, more and more imposters were covered into the geometry coverage of hyperlinks so that the true rejection rate declined. For DS face database, true recognition rate and true rejection rate holds similar changing principle as these on AR face database under the variation of *k* value, which is listed in Table 2. For a practical face recognition algorithm, it is both important to achieve outstanding true recognition and rejection performance. Thus we can choose k=385 and k=350 as an appropriate BPR threshold value to achieve the balance of true recognition and rejection performance in AR and DS face database respectively, where the proposed algorithm can reach the optimal mean true recognition results of 97.94% and 95.66% respectively.

Table 3. Performance comparison of proposed algorithm and other algorithms on AR and DS face database under the same 256-dimensional feature.

Method	PCA+SVM	LPQ+SVM	PCA+BPR	SRC	Proposed
AR Database	90.36%	93.74%	91.63%	94.82%	97.94%
DS Database	89.56%	91.89%	90.76%	92.16%	95.66%

In order to demonstrate the performance of proposed algorithm, Sparse Representation Classifier (SRC) [15], Support Vector Machine (SVM) [16], and PCA based BPR method are adopted here for comparison, where RBF kernel is used in SVM, random sampling dimension reduction method is utilized in SRC, and 96% of the energy of PCA is adopted for PCA plus BPR method respectively. Experiments are all based on the condition of half randomly selected training and testing samples under 256-dimensional feature, and the results are taken the average recognition value of 100 times experiments, as shown in Table 3. It shows that the proposed method outperforms the other three methods in both databases.

4. CONCLUSIONS

A novel disguised face recognition algorithm based on LPQ histogram and hyper sausage neural based BPR method is presented in this paper. The algorithm aims on extracting more robust disguised feature and building a geometry coverage in high-dimensional space to finish the task of recognizing or rejecting disguised faces. Experimental results on both AR face database and disguised face database demonstrate that the proposed disguised face recognition outperforms the other state-of-the-art methods in recognizing disguised faces. However, single feature extraction or multi-scale feature method may not be sufficient to utilize all the information of the disguised face image, so feature fusion can be considered as an improved method in future research to further enhance the recognition efficiency.

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