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Novel Texture Description and Face Identification Methods by Defining Bridle Paths and Using Gabor Phases

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Abstract

Identification based on faces is still a useful method for many applications and face recognition developing is an active research Field. In this paper, a novel face identification method is proposed. The proposed method (Bridle Path on Gabor Phase (BPGP)) is based on extracting texture patterns from phases of the Gabor wavelet. Also, in order to describe the textures, a novel texture descriptor method (Bridle Path) is proposed to extract the features from textures. The Bridle Path method inspired by LBP method and brings some advantages such as lower feature vector length and higher texture description capability in comparison with LBP. Experimental results shows that, Bridle Path texture descriptor is a powerful tool for describing textures and consequently proposed face recognition method (BPGP) yields high identification performance compared to other methods.

Keywords: *Face Identification, Texture Description, Gabor Wavelet*

1. Introduction

Probably because of the wide-range of applications, such as video-surveillance, user authentication and human-computer interaction, Face Recognition is still an active research area. Hence, many different algorithms have been proposed to solve this task over the last 30 years. Nowadays, based on the face image, several different types of systems are able to properly recognize people. The face recognition problem can be formulated as follows: "Given an input face image and a database of face images of known individuals, how can we verify or determine the identity of the person in the input image?".

A face recognition system can be used in two modes: identification and authentication (or verification). In an identification mode, system attempts to establish the identity a given person within different registered or enrolled people by one-to-many matching. On the other hand, in an verification mode, system involves confirming or declining the identity claimed by an individual by one-to-one matching.

Depending on the way the face image is processed, existing face recognition algorithms are often categorized into two groups [1]: appearance-based (also referred to as holistic) and feature-based. In appearance-based method, a high-dimensional vector represents the whole face image.

Typically, feature-based approaches are using a set of local features obtained from the face image to derive a description template of an individual, which will be used for recognition [1]. One successful 2-D face recognition algorithm based on local features is the Elastic Bunch Graph Matching (EBGM) proposed by Wiskott et al [2]. Other successful feature-based approaches are based on generative geometric models, such as GaborJet [3], Pattern of Oriented magnitudes (POEM) [4], Histogram of Gradients (HOG) [7] and histogram of Gabor Phase Patterns (HGPP) [6]. There are also some methods based on statistical generative models, such as Gaussian Mixture Models (GMMs) [7], Hidden Markov Models (HMMs) [8], or it's variant.

Another recent approach are based on Local Binary Patterns (LBPs) [9], where the face is represented by a set of concatenated LBP histograms, each one being computed in a different block of pixels along the image. Recognition is then performed by measuring the similarity between histograms.
The recently proposed local binary pattern (LBP) features are originally designed for texture description [10]. The operator has been successfully applied to face detection, facial expression analysis [11], background modeling [12] and face recognition [9].

In this paper for face recognition task, we propose a new feature-based approach by using the texture patterns of Gabor phases which yields significant identification performance in comparison with other high accurate identification methods. The Bridle Path method is also developed in this paper to extract the features from the texture patterns. Authors show that, the proposed Bridle Path method is related to the LBP intrinsically. It will be shown that, the proposed Bridle Path descriptor is a powerful tool to describe the patterns of images and is more suitable and economic for texture description. Indeed, in the proposed face identification method which we labeled it as BPGP, the features of faces are extracted by using defined Bridle Path method on Gabor Phases.

The remaining of this paper is organized as follows. Section 2 defines the background of Bridle Path descriptor to extract the pattern features from textures and shows its ability to describe textures. Section 3, proposes the new identification method, Bridle Path on Gabor Phases (BPGP) and demonstrated its accuracy in competition with some other accurate face identification methods. The experimental results of the proposed BPGP method are compared with other conventional high accurate face identification methods in section 4, its performance is discussed. Finally, the proposed method in this paper is concluded in section 5.

2. Background

Ojala et al. [10] introduced the Local Binary Pattern operator in 1996 as a means of summarizing local gray-level structure. The operator takes a local neighborhood around each pixel, thresholds the pixels of the neighborhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor. It was originally defined for 3£3 neighborhoods, giving 8 bit codes based on the 8 pixels around the central one. Later the operator was extended to use neighborhoods of different sizes. Using circular neighborhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighborhood. For neighborhoods the notation (P, R) means P sampling points on a circle of radius of R. See Figures 1 and 2 for an example of basic LBP and also the circular (8, 2) neighborhood. During the LBP operation, the value of current pixel, g_c, is applied as a threshold to each of the neighbors, $g_p(p = 0,\ldots, P - 1)$ to obtain a binary number. A local binary pattern is obtained first by concatenating on these binary numbers and then converting the sequence into the decimal number. Formally, the LBP operator takes the form

$$LBPP,R(x,y)=\sum_{p=0}^{p-1} s(gp-gc)2^{p} \tag{1}$$

$$s(x)=\begin{Bmatrix} 0x \;|< 0 \\ 1x \ge 0 \end{Bmatrix} \tag{2}$$

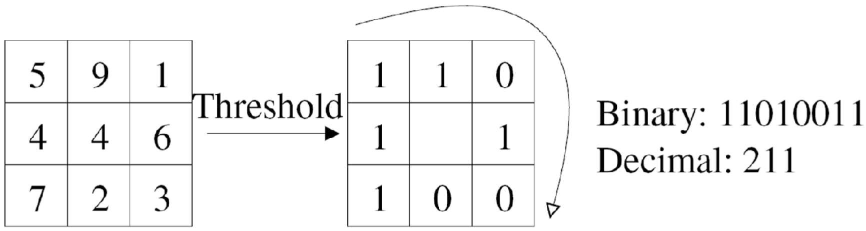


Figure 1. The basic LBP operator

A subset of these 2P binary patterns, called uniform patterns, can be used to represent spot, flat area, edge and corner. The uniform pattern is a binary pattern which contains at most two bitwise transitions. The uniform pattern contains in total (P-1) P+2 binary patterns [9].

Let's look at the LBP operator in a visual manner. Suppose that, we connect the center pixel c to pixel p (p = 0… P- 1) in a (P, R) neighborhood if g_c is larger than g_p. For example, figure 3 shows an example of this visualization in a (8, 3) neighborhood. Therefore, a unique star like shape can be assigned to each LBP decimal value. For a (P; R) neighborhood the number of these shapes is 2^{p}in a non-uniform pattern. Using this imagination behind the LBP operator inspire us to deal with LBP as a tool for coding textures by some predefined star-like primitives. The shape of these primitives is depend on the relationship between the gray values of surrounding pixels g_p and the center pixel g_c.

Similar to the mentioned visualization, a novel histogram descriptor for global feature extraction and description was originally presented by Zhang et all in [13]. They defined three elementary primitives for a 2×2 pixel grid and other complex primitives were computed by matrix transforms. These primitives were used on the image to compute the 2D feature matrix. The Histogram of feature matrix was used to extract and describe the features. In this paper, authors use the idea behind this method and LBP method to modify and develop a new descriptor for feature extracting and texture describing.

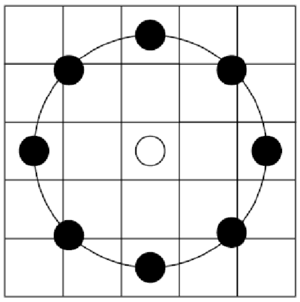


Figure 2. The circular (8, 2) neighborhood

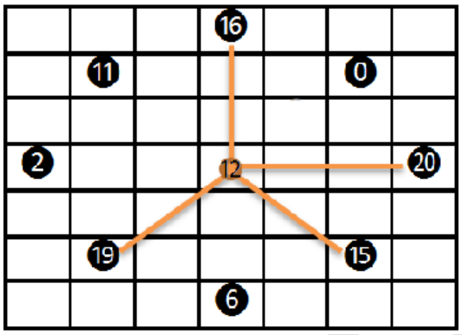


Figure 3. A star-like primitive in the visualization of LBP operator

Assume that f(x, y) denotes an image of size M×N and the 256 gray levels. The centers of pixels are connected to form a primitive according to the gray values from

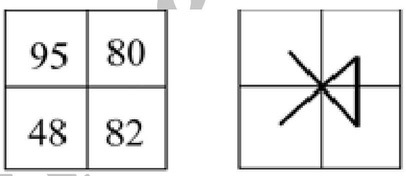


Figure 4. A sample primitive for a 2 £ 2 pixel grid [13]

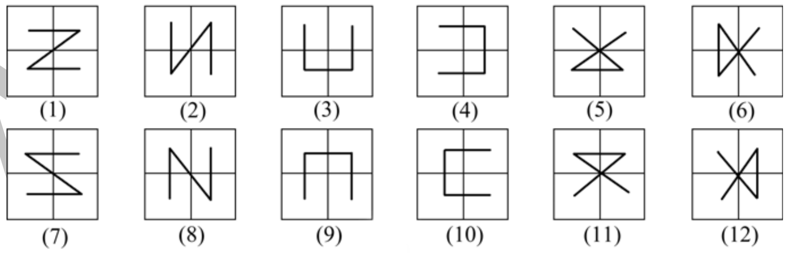


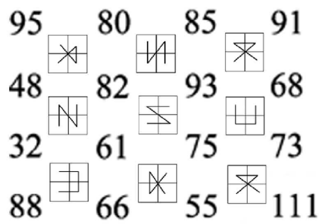
Figure 5. Twelve primitives of a 2 ×2 pixel grid [13]

High to low for a 2 × 2 pixel grid of f(x, y), as shown in figure 4. Consequently, as shown in figure 5 there are 12 primitives for a 2 ×2 pixel grid. Authors in [13] found that if the primitives are invariant to rotation and symmetry, there will be only three different primitives, i.e., (1), (3) and (5). They called these primitives as the elementary primitives.

The feature matrix of size (M -1) × (N - 1) consists of the primitive's number for each 2 ×2 pixel grid of the image. Although, authors in [13] used just 3 elementary primitives for describing the image, we use all of the 12 primitives regardless of the elementary primitives. For example, figure 6 shows an image of size 4 × 4 and its corresponding feature matrix by using 12 defined primitives. Finally, the histogram of the computed feature matrix is used as the feature vector to describe the image.

Now, in order to enhance and improve the representation capability, we extend and modify this method by adding some meaningful innovations which are inspired from LBP method. From now on, we decide to call the mentioned method in [13] as raw method and the following proposed modified method as Bridle Path.

First, while the raw method was proposed with 4 points for a 2 × 2 pixel grid, we define the method with 5 points in an L × L pixel grid. For example, figure 7 shows the pixel grid structure for L = 7. In addition, here, in the 5 Points Bridle Path (BrPa5) method, similar to the raw method, the primitives are formed by connecting the centers



12	2	11
8	7	3
4	6	11

Figure 6. A 4 × 4 image (left) and its corresponding feature matrix (right)

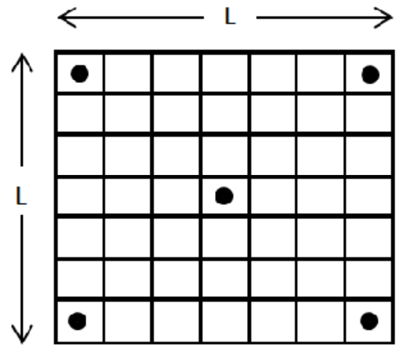


Figure 7. The structure of L × L image pixel grid in the Bridle Path method with L = 7

according to the gray values from high to low. Figure 8 shows two primitives of *5 Points Bridle Path (BrPa5)* in two 3 × 3 grid samples.

Also, we can define *4 Points Bridle Path (BrPa4)* by using raw method on four corner points in the *L*× *L* grid. Since connecting pixels from high to low with respect to the gray values (Decreasing Order) yields same primitive as connecting pixels from low to high (Increasing Order), the number of primitives in Raw (and also 4 Points Bridle Path (BrPa4)) and 5 Points Bridle Path (BrPa4) methods are $12 = \frac{4!}{2}$ and $12 = \frac{5!}{2}$ respectively.

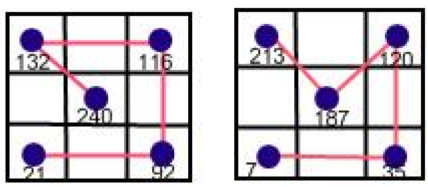


Figure 8. Two samples of 5 points primitives in 5 Points Bridle Path (BrPa5) method

Now, in BrPa5 method the feature matrix is computed by using 60 primitive for each L × L pixel grid of image. Note that, the values of components in the feature matrix of Raw (or BrPa4) method and BrPa5 method are in the range {1, 2,…, 12} and {1, 2,…,60} respectively.

Another difference with raw method is as follow. In the raw method, just a one histogram is extracted from the feature matrix and this histogram is used as the feature vector for representing the image. In Bridle Path methods (BrPa4 and BrPa5), similar to LBP, we segment the feature matrix to P1× P2 non-overlapping patches and the feature vector is constructed by concatenating the extracted histogram from each patch. The extracted feature vector F_{VBrPa} by using BrPa method can be summarized as a concatenation:

$$FvBrPa = [h_{1,1}h_{1,1}h_{1,2}\dots h_{p1,p2}] \quad (3)$$

Where $h_{,j}$ is the computed histogram from patch I,j in feature matrix. So in this manner the length of feature vector of the BrPa4 and BrPa5 methods will be $12\times P_1\times P_2$ and $60\times P_1\times P_2$ samples respectively. Since using different neighborhood size and patching based histogram feature vector construction is so well known in Local Binary Pattern (LBP) based methods [9], authors can confess that the Bridle Path method is inspired by joining two previous works: Raw method and the LBP methods.

Figure 9 shows the achieved performance in face identification experiments (Cumulative Match Characteristics (CMC)) by using Bridle Path method in comparison with some familiar methods (Local Binary Pattern and Histogram of Gradients [5]). Details of the Simulation scenario and used face dataset will be described in the section 4. Note that, in order to fair comparison, since each mentioned methods may have some parameters which can affect their performances, the best result of each method is reported (details of these parameters are in section 4).

Figure 9 shows that, modifying raw method to use different neighborhood size L was so effective and improves its description capability. On the other hand, the BrPa5 method has a comparable identification rate in comparison with others and even we can claim that it is better, because the length of feature vector of BrPa5 is so less than others. The length of the feature vectors of each method is demonstrated in table 1.

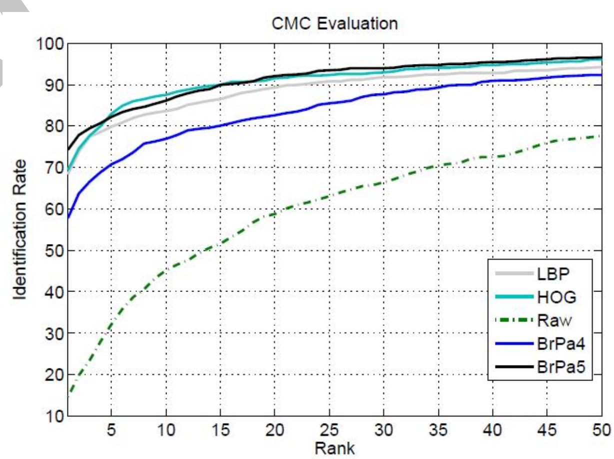


Figure 9. CMC curves for LBP, Raw, Bridle Path, HOG methods

Table1. Performance Comparison between LBP, Bridle Path, HOG methods

Method	CMC(1) %	Length of feature vector
HOG	69.35	111888
LBP	68.34	25600
BrPa4	57.75	1200
BrPa5	74.27	6000

In order to emphasize on the ability of the Bridle Path method versus LBP and Raw method in describing textures, figure 10 shows the CMC identification rate of two methods in a similar parameter settings (neighborhood radius $L = R = 7$ and number of patches 10×10). It can be seen from figure that, while the length of Bridle Path's feature vector was smaller than LBP method, Bridle Path obtains better identification rate.

3. Bridle Path on Gabor Phases (BPGP)

In recent years, Gabor wavelets have been widely used for the face representation by face recognition researchers, because the kernels of the Gabor wavelets are similar to the $2D$ receptive field profiles of the mammal cortical simple cells,

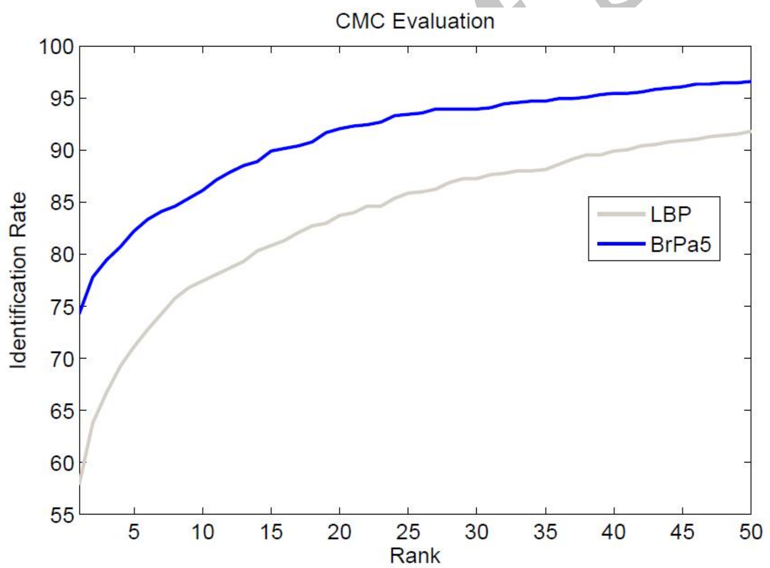


Figure 10. CMC curves for LBP and Bridle Path with similar settings

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 [14]. Authors in [14] show that, the phases of Gabor can be used to describe biometric features.

As mentioned in section 2, presented Bridle Path method can be a powerful tool to extract features from subjects and brings some considerable results in competition with conventional methods. The idea behind BPBP feature extracting method is that, the Bridle Path can encode and present the structure of variations in the phase domain of Gabor scales.

3.1 Gabor wavelets

The 2D Gabor wavelets kernel can be defined as follows [21]:

$$\psi v,\mu(z) == [\frac{\left|\left|k_{v1,\mu}\right|\right|^2}{\sigma^2}] e^{(-\|k_{v,\mu}\|^2\|z\|^2/2\sigma^2)} [e^{ik_{v,\mu}z} - e^{-\frac{\sigma 2}{2}}] \quad (4)$$

Where v and μ define the scale and the orientation (direction) of the Gabor wavelets, respectively; the image position $z = (x, y)$; || .|| denotes the norm operator; and

$$k_{v,\mu} = k_v e^{i\varphi\mu}$$
$$k_v = f_{\max} / \lambda^v \quad (5)$$
$$\varnothing_\mu = \mu(\pi / U)$$

Where λ (typically λ = 2) is the spacing factor between wavelets in the frequency domain; $f$max is the maximum frequency (typically $f_{\max}$= 5) and $\emptyset_\mu$ (typically $\mu(\pi/8)$)) the orientation parameter. The Gabor wavelet scales are obtained by different values of $\mu \in 0,1,\ldots,U-1$ and $v \in 0,1,$ v_{max}.

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

$$O_{v,\mu}(x,y) = f(x,y) * \psi_{v,\mu}(x,y) \quad (6)$$

where * denotes the convolution operator. Each kernel is a product of a Gaussian envelope and a complex plane wave, while the first term in the square brackets in 4 determines the oscillatory part of the kernel and the second term compensates for the DC value. In addition, σ determines the ratio of the Gaussian window width to wavelength. Typically, in face recognition experiments Gabor wavelets are computed in 5 frequencies and 8 orientations.

The Gabor wavelet coefficient $O_{v,\mu}(x,y)$is a complex, which can be rewritten as:

$$O_{v,\mu}(z) = A_{v,\mu}(z).\exp(\theta_{v,\mu}(z)) \quad (7)$$

With one magnitude $A_{v,\mu}(z)$ item, and one phase item $\theta_{v,\mu}$ .It is known that the magnitude varies slowly with the spatial position, while the phases rotate in some rate with positions, as can be seen from the examples in figure 11.

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 [16]. This can cause severe problems for object (face) matching, and it is just the reason that most previous works make use of only the magnitude for face classification. However, the Gabor phase is not worthless. A typical successful application of Gabor phase is the phase-quadrant demodulation coding method proposed by Daugman for iris recognition [17] and face recognition [6].

3.2 Bridle Path on Gabor Phases (BPGP)

We will show that similar to phase-quadrant demodulation coding, Bridle Path can encode the patterns in Gabor plates (Both Phases $\theta_{v,\mu}$ and Magnitudes$A_{v,\mu}$) and it brings some notable results. Assume that, $F_{v,\mu}$ is the extracted feature vector from vth frequency and μth orientation Gabor plate (Phase or Magnitude) by using the Bridle Path methods (BrPa4 or BrPa5). The overall feature vector of the image $FV_{BPGP} = [F_{0,0}\ F_{0,1} \ldots F_{v_{max},U}]$ is generated by concatenating the $F_{v,\mu}s$ for $\mu \in 0$, $1,\ldots,U$- 1 and $v \in 0, 1,\ldots, v_{max}$. Figure 12 shows the CMC curves of face identification simulation by using BrPa4 and BrPa5 on the Magnitudes and phases of a Gabor Wavelet with 3 frequencies and 8 directions. It can be seen that, while the length of feature vectors are the same, extracting features from Phases of the Gabor wavelet is more sufficient and profitable than extracting features from the magnitudes of Gabor wavelet. Since some patches of the face image don't have any meaningful or reliable features with respect to their locations, a simple masking is also applied on the Gabor phase coefficients. Figure 13 shows the shape of the mask that is used to eliminate the unreliable patches. Eliminated patches are located in the black region of the shown mask. The results of using Bridle Path on Gabor Phases (initial BPGP) with 5 frequencies and 8 directions, in comparison with other conventional face identification methods are reported in table 2 and figure 14. The best results of Pattern of Oriented Magnitudes (POEM) and Histogram of Gabor Phase Patterns (HGPP) are also considered in this figure (details of used parameters are concluded in section 4).

Figure 14 shows that, the BPGP method can obtain better identification rate in comparison with other methods. In addition, while both HGPP and BPGP methods are using the Phases of Gabors, the BPGP identifies faces more accurately.

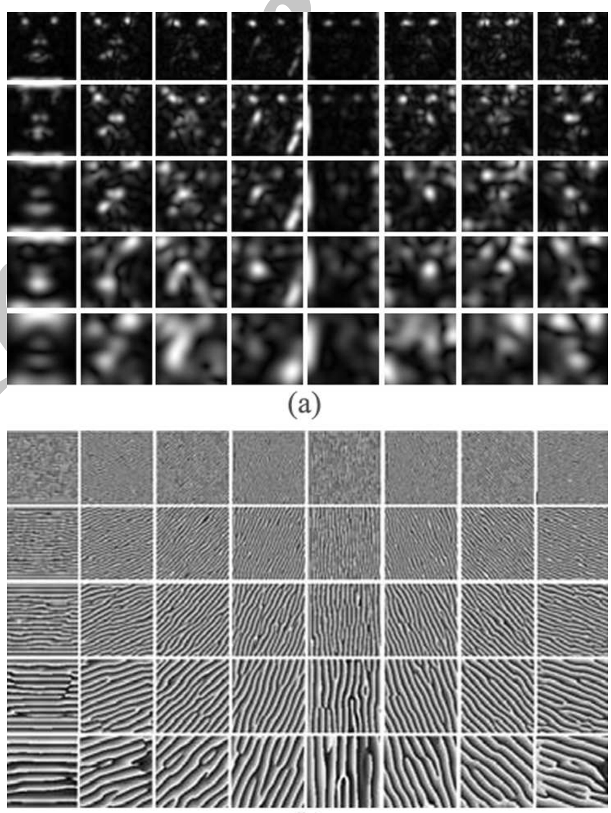


Figure 11.Visualization of the Gabor phase and magnitude in 5 frequencies and 8 orientations. (a) Gabor magnitudes. (b) Gabor phases [6]

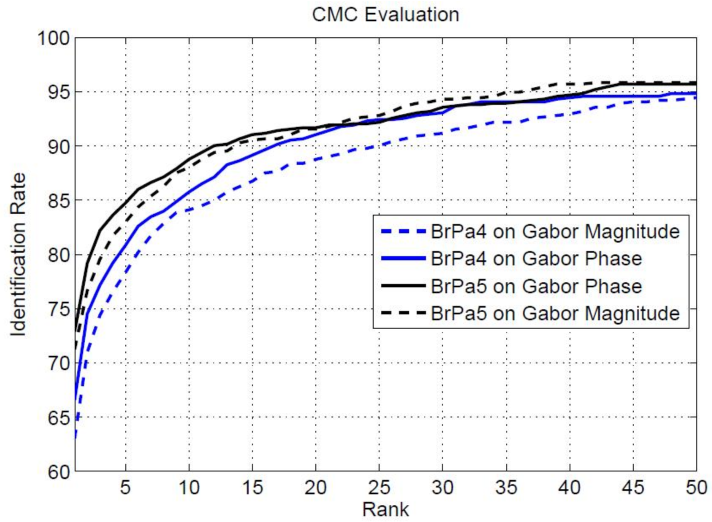


Figure 12. CMC curves by using Bridle Path on Gabor Magnitudes and phases

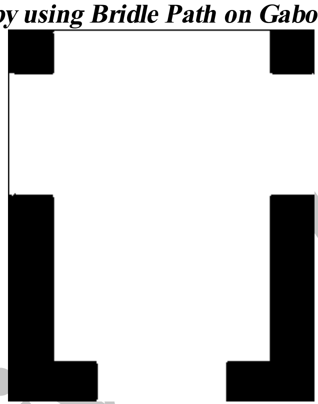


Figure 13. The mask that used for eliminating some unreliable patches

Table2. Performance Comparison between initial BPGP, HGPP, POEM and Hog

Method	CMC(1) %	Length of feature vector
HOG	69.3	111888
HGPP	84.6	331776
POEM	82.0	8496
BPGP4	86.5	30240
BPGP5	88.0	117600

The block diagram of BGPG feature extraction method is shown in figure 15. First, the face image is normalized to compensate the illumination effects [18]. Next, after computing the Gabor wavelet, the phase coefficients of the Gabor wavelet are masked. Finally, the overall feature vector is achieved by concatenating the extracted feature vectors by applying Bridle Path (BrPa4 or BrPa5) on Gabor Phases ($F_{v,\mu}$). Since our idea in BPGP feature extraction method is describing the textures in phases of Gabor wavelet's scales $\theta_{v,\mu}$,it is logical to assign different radius L for different frequency scales v.

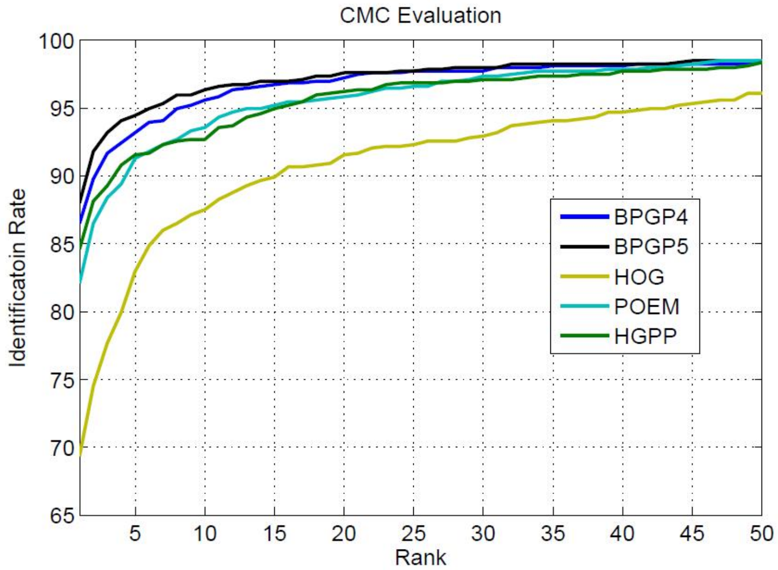


Figure 14. CMC curves for initial BPGP, HGPP, POEM and Hog

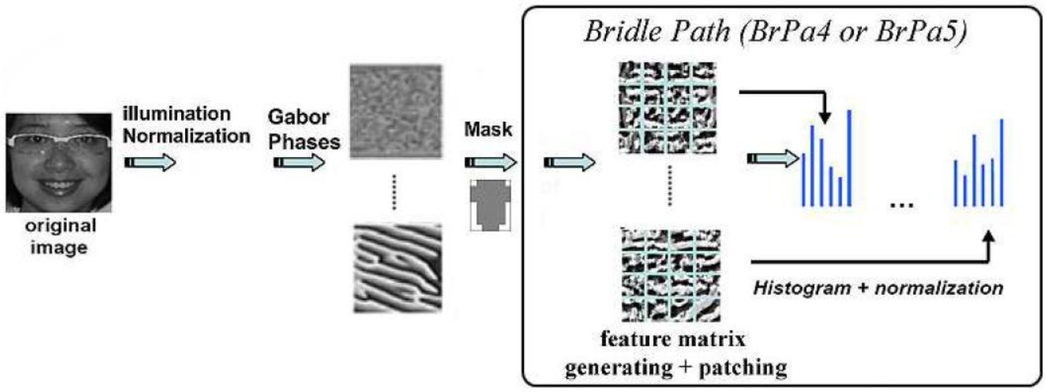


Figure 15. The block diagram of the proposed Bridle Path on Gabor Phase (BPGP) algorithm

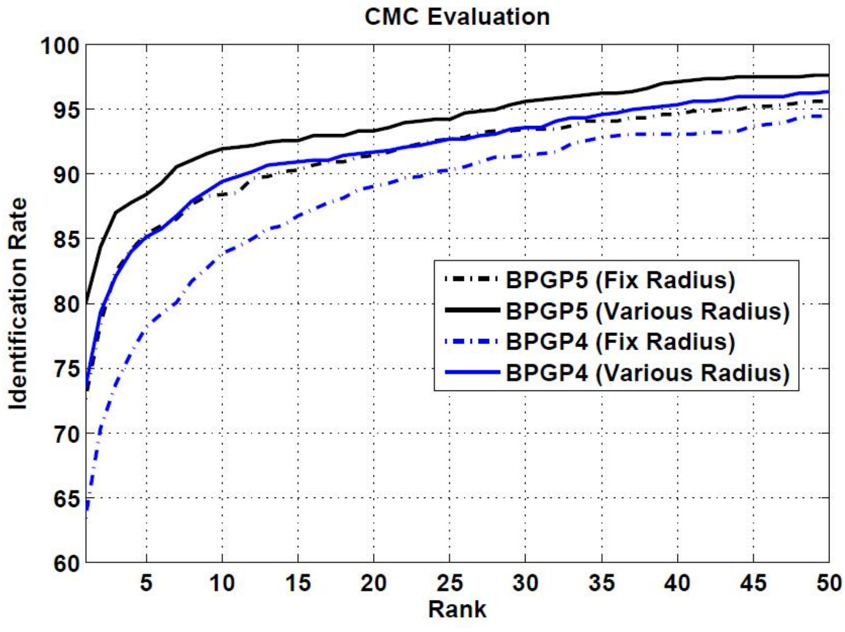


Figure 16. CMC curves for BPGP method with different L

In the other words, consider figure 11b where the frequency in scales goes down from up to down. Obviously, smaller radius *L* is required to describe the textures in higher frequency scales. Consequently, BPGP method proposes using different radius *L* for different frequency scales of Gabor wavelet, larger *L* should assign to lower frequency scales. Figure 16 shows an experiment (BPGP4 and BPGP5 with 3 frequencies and 8 directions) by assigning different radius for different frequency scales. It can be inferred that, using different radius is a meaningful action in BPGP and yields a significant improvement.

The length of the BPGP feature vectors (Le_{fv}) depends on:

- The number of Gabor scales ($U \times v_{max}$)
- The number of patches in each Gabor scale ($P_1 \times P_2$ - *E* patches where *E* is the number of eliminated patches by masking)
- Using 4 points or 5 points Bridle Path (12 or 60 bins for histograms)

If the total number of used patches labeled as $N_p = U \times v_{max} \times (P1 \times P2 - E)$, the length of feature vector Le_{fv} for BPGP4 will be

$$Le_{fv} = 12 \times N_p \quad (8)$$

And similarly for BPGP5

$$Le_{fv} = 60 \times N_p \quad (9)$$

4. Extra Experimental Results

4.1 Used Face Databases

The performance of the proposed face recognition method is validated in this section with respect to identification rate. Used face datasets in this paper are *EEDRA*, *Asian* and *Yale*. Both Yale and Asian face datasets are so conventional in face identification research field, but the EEDRA dataset is collected by us by investigating in 25 different conventional face datasets. The aim in collecting this face dataset was to gather a comprehensive collection of face images which contains many variations, different pose directions, different illumination strength and directions, different expressions, and especially different nations. The EEDRA dataset contains 993 face images of 200 subjects which the locations of eyes are marked manually. Three separate groups include 150 face images with expressions, poses and illuminations.

Other face images (343 face images) are almost full frontal. Some of the full frontal and not-standard face images in EEDRA dataset are shown in figures 17 and 18. The details of used datasets for collecting EEDRA dataset are reported in appendix A. Asian face dataset [20] contains 1819 face images of 107 subjects with a complete set of face variations. These variations include 3 different face expressions, 4 directions of illuminations, 8 directions of pose and even closed eyes. Some of the face images in this dataset are shown in figure 19. Yale face dataset [21] contains 165 face images of 15 subjects with some variations such as eyeglass, illumination and also exaggerated expressions. Some of the face images in Yale dataset are shown in figure 20.

Details of number of used images in our experimental results are reported in table 3. Note that, since proposed method BPGP never used any interclass o intra-class criteria, it can be used for identification scenarios with just single gallery image for each subject.

The following results are experimented in a single gallery face identification scenario. It should be said that all of the reported results in previous sections are attained by using EEDRA face dataset.

Figure 17. Some of the EEDRA full frontal faces images

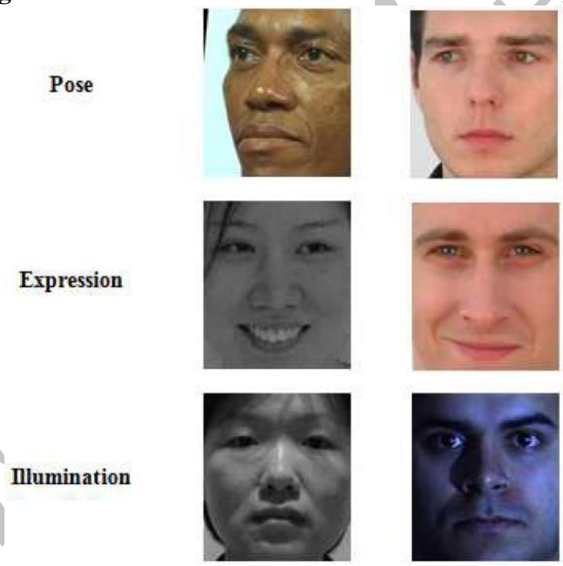


Figure 18. Some of the EEDRA not-standard face images

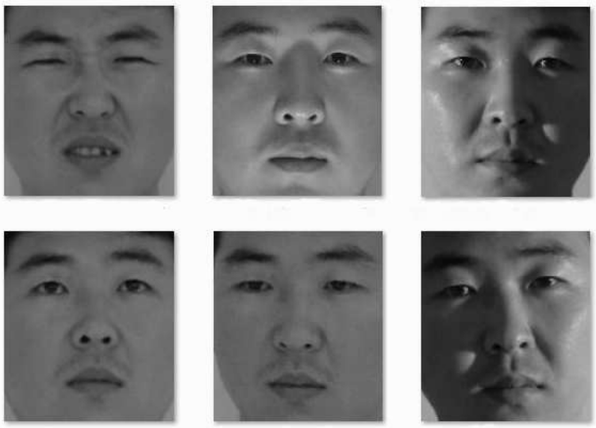


Figure 19. Some of the Asian face images

Figure 20. Some of the Yale faces images

4.2 Results & Discussions

Some of the preliminary experimental results were reported in previous sections. In this section, extra experimental results are described and will be discussed as follow. In the following experiments, the eyes of all of the used face images are located manually and then the faces are resized and cropped from images in a way that there is 80 pixels between left and right eye and the size of cropped face be 180 × 160. In addition, all of the cropped face images are illumination normalized before template extraction. The Gamma normalization method used [18] for this reason. Used distance criterion for measuring the differences or similarities between templates is x^2 distance [19] for histogram based templates and Cosine similarity scores for others.

Table3. The Specifications of Used Face Datasets

Dataset	No. subjects	No. galleries	No. Probes
EEDRA	200	200	793
Yale	15	15	146
Asian	107	107	1070

It is necessary to claim that the performance of BPGP method is compared fairly with other accurate state-of-the-art identification methods such as POEM [4], HGPP [6] and GaborJet [3] in a way that the best achieved performance of them are investigated. Since each method has different effective settings, the settings of each method which cause best identification rate are reported here as follow.

- Local Binary Pattern (LBP) method; 10×10 non-overlap patches (100 patches), 8 sampling points on a circle of radius 4 and using no mapping table (Used in figure 9).
- Histogram of Gradients (HOG) method; The Step of skip is 4, number of bins is 18, and the size of Cell is 8 × 8.
- Pattern of Oriented Magnitudes (POEM) method; Number of orientations is 4, the size of each cell around each pixel is 9 ×9, the diameter of the block for calculation of binary code in LBP is 14, the number of neighbors for calculation of binary code in LBP is 8 and 6 × 6 non-overlap patches (36 patches) for computing histograms.
- Histogram of Gabor Phase Patterns (HGPP) method; Gabor settings: number of frequencies and directions are 2 and 8, the size of the filter's window is 17 × 17, $\sigma = \pi, \lambda = 2 =$ and $f_{max} = \pi/20$.
- GaborJet method; Gabor settings: number of frequencies and directions are 5 and 8, the size of the filter's window is 17 × 17, $\sigma = 2 \times \pi, \lambda = 2$ and $f_{max} = 0.25$;The number of jets is 228.
- Bridle Path on Gabor Phase (BPGP) method; Gabor settings: number of frequencies and directions are 2 and 8, the size of the filter's window is 17 × 17,

$\sigma = \pi, \lambda = 2$ and $f_{max} = \pi/20$; 9×7 non-overlap patches (63 patches) for computing histograms; BrPa Radius for two frequency scales are 11 and 15.

Table 4 reports the results of rank-1 identification rate by using different methods. It can be seen that, in all of the face datasets the BPGP5 method attains best results. BPGP4 is the next method which have better identification rate than others and just in Yale dataset is lower than HGPP method.

Table4. Rank-1 recognition rate comparison with other methods tested on different face image datasets

Method	EEDRA	Asian	Yale
BPGP5	91.4	90.9	89.7
BPGP4	87.8	88.0	80.1
HGPP	84.6	85.4	84.9
POEM	82.0	82.5	69.8
GaborJet	85.8	85.0	73.2

Table5. Performance Comparison between BPGP, HGPP, POEM and GaborJet on Asian face dataset

Method	CMC(1)%	Length of Feature Vector	Time of Template Extraction
BPGP5	90.9	47040	1314 ms
BPGP4	88.0	12096	1186 ms
HGPP	85.4	331776	2387 ms
POEM	82.5	8496	479 ms
GaborJet	85.0	9120	859 ms

Figures 21, 22 and 23 demonstrate the achieved CMC curves of the BPGP, HGPP, POEM and GaborJet methods tested on EEDRA, Asian and Yale face datasets, respectively. Mentioned figures implies that, the BPGP method (and specially BPGP5) attains best identification rate in comparison with others. The Yale dataset just has 15 gallery subjects and so its CMC curve will be ended in 15th rank. In order to compare and discuss about the identification results of methods, table 5 is reported here to which investigates the rank-1 identification rate of the methods in Asian face dataset with respect to their length of feature vector (template) and elapsed time for feature extraction. By considering table 5, it can be inferred that as mentioned before, the proposed BPGP methods is a reliable and economic method, because not only its identification rate is the best, the length of its feature vector and also the consumed time for generating feature vector is less than the second high performance method HGPP. Note that, both HGPP and BPGP methods are using Gabor phases for feature extracting. Finally, the GaborJet method is a sufficient and a good choice for fast identifying with low length of feature vector.

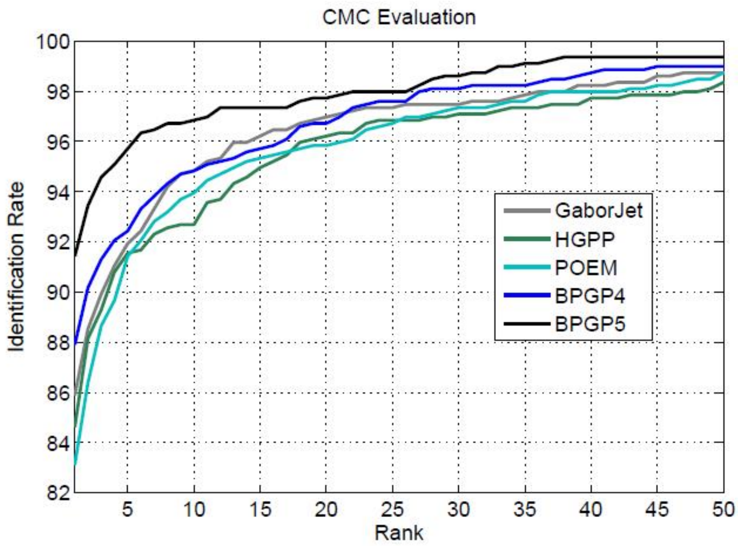


Figure 21: CMC curves for BPGP, HGPP, POEM and Gaborjet tested on EEDRA face dataset

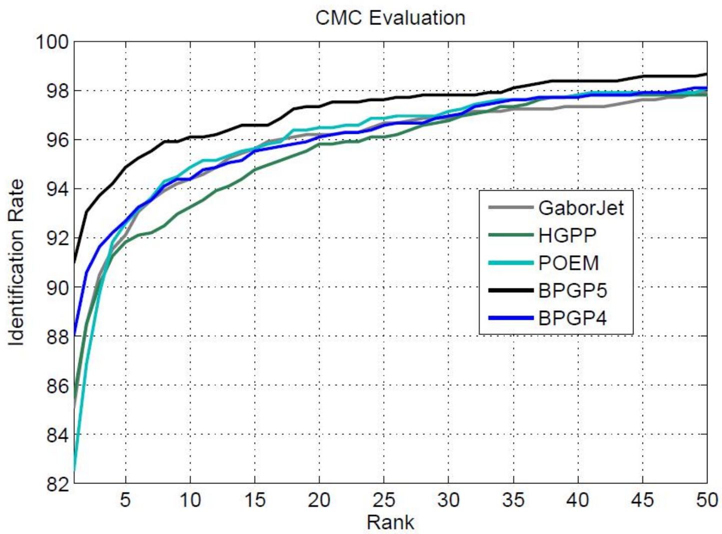


Figure 22: CMC curves for BPGP, HGPP, POEM and Gaborjet tested on Asian face Dataset

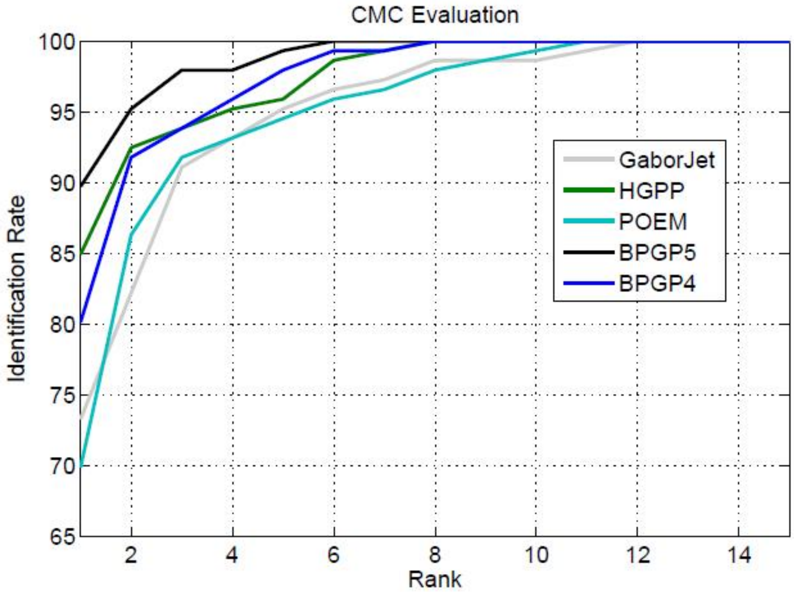


Figure 23: CMC curves for BPGP, HGPP, POEM and Gaborjet tested on Yale face dataset

5. Conclusion

In this paper, a novel texture descriptor method, Bridle Path is proposed which inspired by LBP method. Results show that, while the length of feature vectors of Bridle Path is smaller than LBP, the Bridle Path method is so more powerful than LBP in describing textures. Also, in this paper in order to emphasize on the Bride Path abilities, Bridle Path deployed for face recognition task. In the proposed face identification method (BPGP), Bridle Path method is used to extract texture features from the phases' of Gabor wavelet. Experimental results show that, BPGP face recognition method yields high identification performance compared to other methods.

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Appendix A. EEDRA Face Dataset

Authors collect a comprehensive face database from available face images in several face databases to cover different parameters. Although expression, pose, illumination and nationality are considered in EEDRA database, all of the face images in the EEDRA face database are almost frontal and the large deviations from frontal faces are prevented. The EEDRA face database can be obtained in the mentioned link address in the table. Details of used face databases, number of images, number of subjects and their web links are as follow:

Face Database Name	No. of Images	No. of Subjects
EEDRA	993	200
Asian Faces	90	10
Colorferet	227	36
Inria	57	8
PIE	189	15
YaleB	37	4
JAFFE	22	4
Caltech	41	4
Georgia	19	3
Indian	32	5
PUT	79	10
Local Iranian	200	100

Face Database Name	Link
EEDRA	*http : //icode.ir/EEDRA-Face-Dataset*
Asian Faces	*https : //sites.google.com/site/asianfacedb/*
Colorferet	*http : //www.nist.gov/itl/iad/ig/colorferet.cfm*
Inria	*http : //pascal.inrialpes.fr//data/human/*
PIE	*http : //www.ri.cmu.edu/*
YaleB	*http : //cvc.yale.edu/projects//yalefacesB/yalefacesB.html*
JAFFE	*http : //www.kasrl.org/jaffe.html*
Caltech	*http : //www.vision.Caltech.edu//html -files/archive.html*
Georgia	*http : //www.anefian.com/research/facereco.htm*
Indian	*http : //vis – www.cs.umass.edu/vidit/IndianFaceDatabase/*
PUT	*https : //biometrics.cie.put.Poznan/*