BGP Face Recognition Method Based on Heuristic Information

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ABSTRACT

Binary gradient pattern (BGP) is a concise and efficient descriptor for face recognition which is robust to light, expression and occlusion. It has achieved remarkable results in face recognition applications. However, BGP descriptor is a universal operator, which does not reflect the particularity of human face in the process of face recognition. This paper draws on the experience of human face recognition based mainly on facial features (including eyes, nose and mouth), and proposes a method of face recognition based on heuristic information. This method firstly determines the general location of the above facial features according to human experience. Secondly, BGP operator is used to extract the features of the face, and we divide faces into several sub-blocks to obtain the histogram features of each sub-block. Finally, the features corresponding to the positions of the features are weighted. The method is fully validated in Yale and ORL libraries. Compared with the original BGP method, the recognition accuracy and robustness are significantly improved.

Keywords: Binary gradient pattern (BGP), heuristic information, face recognition

1. INTRODUCTION

Face recognition, refers to the computer technology that uses analysis and comparison of facial visual features information for identification. Generalized face recognition includes a series of related technologies to construct face recognition system, including face image acquisition, face location, face recognition preprocessing, identity verification and identity search. Narrow face recognition refers to the technology or system of identity verification or identity search through faces. In recent years, face recognition has always been a hot issue in the field of image processing, computer vision, pattern recognition and cognitive science, and has the characteristics of obvious discrimination and easy access. It is widely used in security verification, quick payment, video survey, identification and other occasions.

After years of development, a variety of face recognition algorithms have been put forward, which can be summarized and divided into the following categories: 1) The recognition methods based on the local features of human faces, such as Bayesian method [1], Fisherfaces method [2], Binary Gradient Pattern (BGP) [3], elastic graph matching [4] and Local Binary Pattern (LBP). 2) Recognition methods based on global features of face, such as Linear Discriminant Analysis (LDA) [6], Principle Component Analysis (PCA) [7], Independent Component Analysis (ICA) [8] and other methods. 3) Approaches based on the combination of global features and local features, such as the method based on the combination of eigenfaces and facial features [9]. Methods based on deep learning are also used in face recognition, for example, the facenet is proposed and applied in the face field [10] [11].

In the recognition method based on local features of human face, BGP is a concise and efficient face descriptor. Structural BGP extracts the structural gradient pattern as a binary string for face recognition, and experiments prove that the descriptor is robust to light, shelter, etc. However, BGP is a universal descriptor. When it is used to describe and identify human faces, the particularity of human faces isn’t shown and human prior knowledge and heuristic information aren’t utilized. This paper presents a heuristic face recognition method based on BGP. This method is improved on the basis of BGP algorithm. By applying the prior knowledge and heuristic information that facial information is particularly important when human recognizes faces, we apply weights to the parts corresponding to facial positions (including eyes, nose and mouth) in the BGP descriptor. The thesis systematically analyzes the theoretical basis of BGP algorithm, evaluates the advantages and disadvantages of BGP comprehensively, proposes some improvements for the shortcomings, constructs a BGP face recognition method based on heuristic information, and verifies the accuracy of the method using public face libraries such as Yale and ORL Library. Compared with the original BGP algorithm, recognition accuracy has been significantly improved.
2. BINARY GRADIENT PATTERN(BGP)

2.1 The basic thinking of BGP

BGP is a concise and efficient face descriptor proposed by Weilin and Hujun [4] in the 2017 Pattern Recognition article "Robust face recognition with structural binary gradient patterns". The idea stems from the new Gradientfaces descriptor proposed by Zhang et al. This descriptor replaces the pixel intensities with the image gradient direction (IGO) to describe the human face in order to achieve robustness against changes in illumination. Binary gradient model measures the relationship between local pixels in the image gradient domain and effectively encodes the underlying local structure into a set of binary strings, which not only increases the discriminative power, but also greatly simplifies the computational complexity.

2.2 The algorithm principle of BGP

In order to find out the potential structure of the gradient domain, BGP calculates the gradient of the image from multiple directions and encodes it into a series of binary strings, which can represent slight boundary changes and texture information. Therefore, BGP has strong discriminability and can achieve excellent recognition accuracy even facing occlusion, light and expression change, etc.

The basic principle of BGP is as follows:

1. Given a central pixel and a series of local neighboring pixels (such as the eight adjacent pixels in Figure 1)
2. Then, based on Equation 1, a pair of binary encodings (primary and secondary) can be calculated based on two symmetric neighboring pixels in each direction. As shown in (b) (c) of Fig. 1, four pairs of binary numbers are obtained from four directions G1, G2, G3, and G4

\[
B_i^+ = \begin{cases} 
1 & \text{if } G_i^+ - G_i^- \geq 0 \\
0 & \text{if } G_i^+ - G_i^- < 0 
\end{cases}
\]

(1)

\[
B_i^- = 1 - B_i^+ 
\]

i=1,2,...,k

3. Finally, the label of the center pixel is obtained through four main binary codes, that is, BGP representation as formula (2).

\[
L = B_1^+ B_2^+ B_3^+ B_4^+ 
\]

(2)

Then it is transferred into a decimal number such as formula (3)

\[
\tilde{L} = \sum_{i=1}^{k} 2^{-i-1} B_i^+ 
\]

(3)

Eight binary numbers are obtained in all four directions, but the major and auxiliary binary numbers in each direction are always complementary. Therefore, only one binary bit is required for each direction. For the sake of conciseness, only the main binary is needed to calculate the label (according to equation (3)).
2.3 The applicable conditions of BGP

Binary gradient pattern applies to grayscale images, which should be firstly converted to grayscale images for color images. Since each encoded value contains the information of the neighborhood pixel relationship, not just the pixel's own intensity information during the process of encoding the image with BGP, BGP encoded images are more robust to various environmental changes, especially with strong light invariance.

2.4 The advantages and disadvantages of BGP

BGP has the characteristics of simple calculation, strong discriminability and good robustness, which is very suitable to face recognition. And the BGP feature has the following advantages: First, BGP is defined in the image gradient pattern, and it has a good gradient characteristic, which can effectively deal with changes in light intensity and so on; Second, structural model and multi-spatial resolution are used in BGP. Structured BGP is equivalent to the edge detector, which is the key to accurate identification and concise expression. Meanwhile, the multi-spatial resolution strategy increases the ability of descriptors to cover pixels with different radius in neighborhoods. However, BGP operator is a kind of universal operator. It does not reflect the particularity of human face in the process of recognizing human face, and it ignores some structural information and heuristic information of human face. What’s more, the experiment information is not utilized that human use when recognizing faces. The idea of the proposed method for face recognition based on heuristic information originated from this.

3. BGP FACE RECOGNITION METHOD BASED ON HEURISTIC INFORMATION

3.1 The basic thinking

The BGP method can robustly, stably and accurately identify human faces, but there are problems that the method is stylized and lack of intelligence. When human recognize faces, facial information and structural information is important. An important manifestation and development direction of artificial intelligence is to make the computer to learn the way of human thinking and human behavior. Therefore, this paper proposes BGP face recognition method based on heuristic information. This method makes the computer better utilizes the heuristic information and prior knowledge of human face during the process of recognizing human face, making full use of the important structure information such as facial feature information, enhancing the intelligent level of BGP face recognition method.

3.2 Formalization

For the convenience of expression, the parameters involved in the method of BGP face recognition based on heuristic information are formalized as shown in Table 1.

| Parameter                          | Symbol | Illustration                        |
|------------------------------------|--------|-------------------------------------|
| Neighborhood radius of BGP         | R      | Usually R=1 or 2                    |
| The number of neighborhood pixels of BGP | P      | P=8*R                               |
| Number of blocks                   | M*N    | Usually M=N                          |
| The statistical histogram dimensions for each sub-block | d      | Only related to R                    |
| Histogram dimensions of face pictures encoded by BGP | d1     | This value is equal to M * N * d    |
| Facial weight coefficient          | w      | The importance of facial features(including eyes, nose and mouth) |

3.3 Algorithm description

3.3.1 BGP method to find eigenvectors

For a grayscale image, we can get the eigenvector (dimension d1) with the binary gradient pattern. The algorithm flow is as follows.
We will elaborate the process of getting feature vectors with BGP in the following part. Suppose the neighborhood radius $R = 1$, then the number of BGP neighborhood pixels $P = 8$, the number of blocks $M \times N$ ($M = N = 5$). Since 8 neighborhood pixels determine 8 directions (4 main, 4 auxiliary), the BGP code value of any one central pixel should be a 4-digit binary number, converted to a decimal value of 0 to 15. There are 8 structural patterns for the 16 modes, and the non-structural patterns are ignored. Then the dimension of BGP histograms is 8 for each sub-block ($d=8$). The histogram dimension of face image after BGP coding should be $d_1 = 200$ ($5 \times 5 \times 8$).

After a gray image is extracted from the BGP features, a BGP feature image is obtained. Figure 3 shows a BGP feature image after being divided into 5*5 blocks. The order of 25 sub-blocks is from left to right and top to bottom.

| $A_1$ | $A_2$ | $A_3$ | $A_4$ | $A_5$ |
|-------|-------|-------|-------|-------|
| $A_6$ | $A_7$ | $A_8$ | $A_9$ | $A_{10}$ |
| $A_{11}$ | $A_{12}$ | $A_{13}$ | $A_{14}$ | $A_{15}$ |
| $A_{16}$ | $A_{17}$ | $A_{18}$ | $A_{19}$ | $A_{20}$ |
| $A_{21}$ | $A_{22}$ | $A_{23}$ | $A_{24}$ | $A_{25}$ |

Fig 3. The order of BGP feature image blocks

The statistical histogram of 8 structural BGP in one sub-block is shown in Figure 4, non-structural BGP is ignored. It can be seen that the histogram is a normalized histogram, which can effectively reflect the frequency of appearance of the eight structural patterns in the sub-block.
X_{A1} is used to represent the statistical histogram of the A1 sub-block, that is, the frequency of occurrence of the eight structural patterns, expressed as an 8-dimensional row vector. Similarly, X_{Ak} represents a statistical histogram of the Ak sub-block. Histograms of all sub-blocks are stitched together to form the final vector P, which is the feature vector calculated from the binary gradient pattern of this gray image. The eigenvector P is calculated as Eq (4)

\[ P = [X_{A1}, X_{A2}, \ldots, X_{Ak}, \ldots, X_{A25}] \]  

(4)

### 3.3.2 BGP face recognition method based on heuristic information

For a face image, the general position information of facial organs including eyes, nose, mouth is fixed, which is the prior knowledge of human beings. And the knowledge becomes heuristic information to optimize the algorithm after being introduced into computer face recognition.

Usually the relative position of facial features in the face is shown in Figure 5. It is divided into 3 equal parts in vertical direction, and 5 equal parts in horizontal direction. The eyes are in the middle one-third of the portrait in vertical direction, and in the second and fourth one-fifth of the horizontal direction. The nose and mouth are in the second and third one-third of the longitudinal direction, and in the middle one-fifth of the lateral direction.

The proposed method based on heuristic information in this paper is based on the empirical knowledge and enlightening information of the facial features on the face in Figure 5, combined with the blocking rules of the BGP method. Because the eye is located closer to the first one-third of the longitudinal direction, in order to enhance the robustness of the facial features determination, the position of the facial features is adjusted slightly.

As shown in Figure 6, It is divided into 6 equal parts in vertical direction, and 5 equal parts in horizontal direction. The eyes are at the second and third one-sixth of the portrait in vertical direction, and at the second and fourth one-fifth of the landscape. The nose and mouth are at the third to the sixth one-sixth of the longitudinal direction, and at the middle one-fifth of the lateral direction.
The number of blocks in the BGP method is \( M \times N \). The ordinal number of blocks occupied by eyes, nose and mouth is shown in the following pseudocode:

1) The ordinal number of BGP blocks occupied by the left eye
   - for \( i = \lfloor M/6 \rfloor : \lfloor M/2 \rfloor \) (\( \lfloor \rfloor \) represents integral symbol)
     - for \( j = \lfloor N/5 \rfloor : \lfloor N/2 \rfloor \)
       - ordinal number = \( (i-1) \times N+j \)
   end
   end

2) The ordinal number of BGP blocks occupied by the right eye
   - for \( i = \lfloor M/6 \rfloor : \lfloor M/2 \rfloor \) (\( \lfloor \rfloor \) represents integral symbol)
     - for \( j = \lfloor N/3 \rfloor : \lfloor N/2 \rfloor \)
       - ordinal number = \( (i-1) \times N+j \)
   end
   end

3) The ordinal number of BGP blocks occupied by the nose and mouth
   - for \( i = \lfloor M/6 \rfloor : \lfloor M/2 \rfloor \) (\( \lfloor \rfloor \) represents integral symbol)
     - for \( j = \lfloor N/5 \rfloor : \lfloor N/2 \rfloor \)
       - ordinal number = \( (i-1) \times N+j \)
   end
   end

As shown in Figure 6, \( M = N = 5 \). According to the pseudo code, the BGP ordinal numbers occupied by eyes, nose, and mouth are A2, A7, A12, A4, A9, A14, A8, A13, A18, A23. When statistics histogram feature is calculated by BGP method, the histogram features of the BGP blocks occupied by the above official positions are weighted, and the weight coefficient size represents the degree of importance that the computer considers the facial features to be relative to other positions on the face. According to the above description, for the 5 * 5 block method, the facial feature vector obtained by the BGP face recognition method based on heuristic information is as shown in formula (5):

\[
P = [X_{A1}, W^1X_{A2}, X_{A3}, \ldots, X_{A5}, W^5X_{A6}, \ldots, W^9X_{A10}, \ldots, W^{14}X_{A15}, X_{A16}, X_{A17}, X_{A18}, X_{A19}, X_{A20}] \]

(5)

4. EXPERIMENTAL RESULTS AND ANALYSIS

In order to validate the heuristic information-based BGP face recognition method proposed in this paper, experiments are performed on standard face libraries such as Yale and ORL.

4.1 Standard Face Library Introduction

Yale library contains 15 subjects, each with 11 positive face images, a total of 165 face images, including the light, facial expression, occlusion and other changes. A part of Yale face image is shown in Figure 7.
OVL face database has 40 objects of different ages, different races and different genders. Each person has 10 images with a total of 400 grayscale images with a size of 92 * 112. A Part of the face images of a person in the ORL library is illustrated in fig 8.

![Fig 7. A Part of images of one person in Yale](image1)

ORL face database has 40 objects of different ages, different races and different genders. Each person has 10 images with a total of 400 grayscale images with a size of 92 * 112. A Part of the face images of a person in the ORL library is illustrated in fig 8.

![Fig 8. A Part of images of one person in ORL](image2)

### 4.2 The Size of Divided Sub-images

The above-mentioned BGP feature extraction method is based on the premise that the original image is divided into non-overlapping sub-images. The selection of sub-image size is very important because it has some influence on the recognition result. If the sub-block is too small, the extreme case is the original image, so that it cannot reflect the local information of the image. If the sub-blocks are too many, the extreme case is that each pixel is a sub-image, which greatly increases the computational complexity, and easy to introduce noise.

In order to find the appropriate number of blocks in the Yale and ORL libraries, we apply the basic BGP method in the two databases with radius R of 1 and 2, respectively. The experimental results on the Yale and ORL libraries are shown in Table 2 and Table 3, respectively.

| Radius | 4*4 | 8*8 | 16*16 | 32*32 | 64*64 |
|--------|-----|-----|-------|-------|-------|
| 1      | 0.5133 | 0.6467 | 0.68 | 0.72 | 0.5667 |
| 2      | 0.5667 | 0.6133 | 0.6733 | 0.72 | 0.633 |

Table 2. The effect of number of sub-blocks and radius on recognition rate of Yale library

| Radius | 4*4 | 8*8 | 16*16 | 32*32 | 64*64 |
|--------|-----|-----|-------|-------|-------|
| 1      | 0.5133 | 0.6467 | 0.68 | 0.72 | 0.5667 |
| 2      | 0.5667 | 0.6133 | 0.6733 | 0.72 | 0.633 |

Table 3. The effect of number of sub-blocks and radius on recognition rate of ORL library
It can be seen from Table 2 and Table 3 that when the number of blocks M * N is 8 * 8, 16 * 16, 32 * 32, and the radius R is taken as 1, then the recognition rate is relatively high.

4.3 The influence of weighting coefficient on recognition rate

We experiment separately in Yale and ORL face libraries. Radius R is taken as 1, and the number of blocks M * N is 8 * 8, 16 * 16, 32 * 32, and the weighting coefficient w is from 1 to 10. The experimental results are shown in Figure 9 and Figure 10.

**Fig 9. The influence of weighting coefficient on recognition rate in Yale library**

**Fig 10. The influence of weighting coefficient on recognition rate in ORL library**

In Figure 8 and Figure 9, the method is equal to the original BGP method when the weighting coefficient is 1. As can be seen from the two graphs, the recognition rate is significantly improved using BGP face recognition method with weighting coefficient compared to that of the original BGP method. At first, with the increase of the weighting coefficient, the importance of the five features increased, and the recognition rate improved. Afterwards, the recognition rate
tended to be stable, and the recognition rate was nearly equal to that of the original BGP. Generally, when the weighting coefficient is about 3 or 4, the recognition rate increases most obviously.

4.4 Conclusion

This paper presents a heuristic method based on BGP face recognition. Through learning from the prior knowledge and heuristic information that the eyes, nose and mouth are relatively important and they are relatively fixed when human faces are recognized, we take advantage of the location information and structure information of the facial features. Finally, the weighting coefficient is added to the BGP block histogram features of the five organs combined with the basic BGP method. Experimental analysis was performed on Yale and ORL. The results showed that the BGP face recognition method based on heuristic information added with weighting coefficient enhances the face representation ability, improves the robustness of the algorithm, and significantly increases the face recognition rate. In conclusion, this method is effective and feasible.

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