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Simulation and Application of Weighting Vector Machine Algorithm in Face Recognition

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Abstract

The author proposes a weighted algorithm supports local binary pattern vector machine (LBP) focusing on face recognition feature extraction problem. First LBP of face images and gradient LBP features were extracted, then they were weighting combined to form facial feature vectors; finally the support vector machine was used to build face recognition classifier, and more than one face database were used for simulation. The results show that compared to other face recognition algorithm, the algorithm in this paper not only has improved the overall average face recognition rate, but also improved the efficiency of face recognition.

Keywords*: local binary patterns; in-depth image analysis; support vector machines; weighted merger*

1. Introduction

Because the human face is unique, non-contact and can not be copied, *etc.*, face recognition is an important biometric identification technology, which is widely used in business, law, military, security and other fields, and has become a hot research topic in the field of computer vision and pattern identification [1].Because face recognition is pattern recognition problem in image processing, and it is a typical multi-classification problem, hence before we establish the face classifier, we must first extract facial classes feature description. The feature extraction directly affects results of recognition[2]. For facial feature extraction problem, enthusiasts and experts at home and abroad have conducted extensive, in-depth research, and proposed a number of facial feature extraction algorithm [3].The classic facial feature extraction methods are: principal component analysis (PCA), linear discriminant analysis (LDA), independent component analysis (ICA) [4-6]; these algorithms are one class linear feature extraction algorithm, and can not describe nonlinear characteristics inherent in human face image; when the face image is covered, or lighted, the useful extraction information of facial feature is quite small, with poor illumination robustness [7]. In recent years, some scholars have proposed extraction algorithm based on local binary pattern (LBP) facial features, which provides a new idea for human face features extraction. A lot of studies show that, LBP algorithm could obtain better results than the traditional feature extraction [8-10]. Based on LBP, many scholars improve and deform it, such as literature [11] that introduced face depth image into the LBP algorithm, and proposed 3DLBP. It has improved the accuracy of face recognition; however, the algorithm has too long characteristic length, and its coding algorithm is unstable [12].

In order to improve recognition accuracy, the author has proposed a face recognition combined weighted algorithm based on LBP and gradient LBP, and use more than one face database to conduct simulation experiments so as to test the effectiveness of the proposed algorithm. The test results show that the algorithm not only improves the overall

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average face recognition rate, but also improves the efficiency of face recognition.

2. Proposed Face Recognition Algorithm Workflow

In this paper, the method of face recognition workflow has been shown in Figure 1. First LBP features of face images and gradient LBP were extracted, and then combine them to form facial feature vectors by weighting; finally establish face recognition classifier out of SVM and output recognition results.

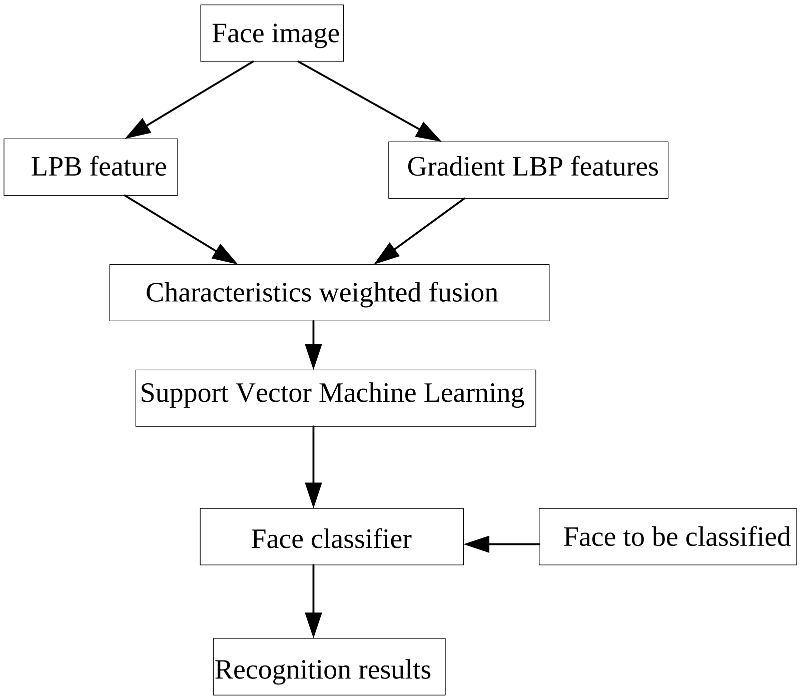

Figure 1. Proposed Face Recognition Algorithm Workflow

3. Face Characteristics Indication

3.1LBP

LBP operator is proposed by Ojala *et al.* in 2002. This method has a small computational complexity, rotation invariant features and other advantages in terms of texture feature extraction, and has achieved very good results in texture classification, face image analysis, image retrieval, and other fields. The original LBP operator in 3 × 3 window has used the center pixel and its neighboring partial image pixel to conduct threshold calculation, so as to obtain the neighborhood binary code. Then string together in one direction to transfer the Binary into Decimal, resulting in a new pixel gray value [13]. LBP code is calculated as follows:

$$LBP_{P,R}(x_c, y_c) = \sum_{i=0}^{p-1} S(g_i - g_c)2^i$$
$$S(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{1}$$

$$S(g_i - g_c) = \begin{cases} 1, g_i - g_c \geq 0 \\ 0, g_i - g_c < 0 \end{cases} \tag{2}$$

(xc, yc) is the coordinate of center pixel C in the eight neighbor; the center pixel value is gc; gi (i = 1,2, ..., 8) represents the pixel value of the neighborhood points around the center point; S (gi -gc) represents threshold operation, the value of the neighborhood point is greater than the value of the center pixel is 1, otherwise 0. R represents the radius of the neighborhood, P refers to the number of pixels on the circumference take R as the radius, gc as the center point. Figure 2 is a binary encoding LBP.

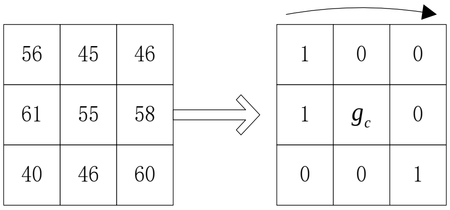

Figure 2. LBP Binary Coding

According to the LBP algorithm formula, it not only highlights the more obvious changes in the gray edge direction, but also describes relatively tiny minutiae of the partial image pixel changes, reflecting the good LBP texture characterization capabilities.

3.2. DLBP

The depth difference information (depth difference, DD) is dedicated to the face depth image analysis; due to the smoothness of depth face image changes, the texture and, the environmental conditions of neighboring point may be randomly different. Literature [14] results show that when R = 2, more than 93% points each other has less than 7 DD; therefore, DD can be expressed using only three digits, all | DD |> 7 are set to 7. Use i1 to represent the DD sign bit, i2, i3, i4 represent the absolute value of DD, then:

$$i_1 = \begin{cases} 1 & DD \geq 0 \\ 0 & otherwise \end{cases} \tag{3}$$

$$|DD| = i_2 * 2^2 + i_3 * 2^1 + i_4 * 2^0 \tag{4}$$

Then divide four digits into four layer; for each layer, all the surrounding pixels are connected to the corresponding bit DD, and a LBP code is generated. There are a total of four LBP code {N1, N2, N3, N4}, called three dimensional local two value model (3DLBP).

3.3. Gradient LBP

Since the smoothness of the depth face image, most of the image depth difference is less than 7, so, 3DLBP has included original LBP and the face image depth difference into coding features, which can represent the depth image more effectively; however, there are several disadvantages in the algorithm : (1) the characteristic length is too large; (2) coding algorithm is unstable; (3) the inherent connection between the DD symbols and the absolute values have lost.

Based on the above analysis, the author proposed a gradient-LBP (G-LBP), which introduce DD into the original LBP, and has overcome all the drawbacks mentioned in 3DLBP. Consider each direction separately calculated in whole image LBP, which generates eight differential depth image corresponding to eight directions, for LBP8, 1 use (Figure 2). At each position (xc,yc), we use Formula (1) to calculate LBPP,R code, P center pixels corresponding to the guide depth difference are :

$$ODD_{p=0\ldots P-1}^{P,R,p} = \max(\min(g_p - g_c, 7), -8) \tag{5}$$

Wherein, ODDP, R, p is the guide depth difference of the depth image; gp is the depth value of central pixels surrounding a circle of radius R on the circle (xp,xp); gc is the depth value of the center pixel.

After obtaining P guide depth difference images, construct the histogram in each depth difference images in each direction to produce P histograms; in each histogram there are 16 bins, from -8 to 7, and then combine them in series to form P histogram information, hence form a single guide depth difference histogram; the results are shown in Figure 3.

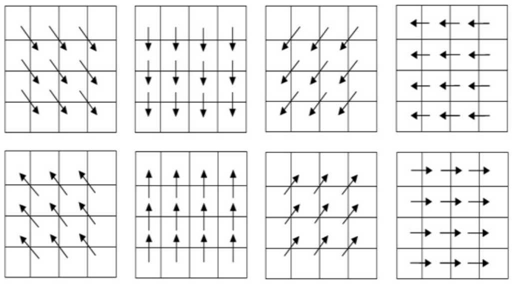

Figure 3. Depth Difference of LBP8,1 Direction

3.4. Weighted Combine LBP and Gradient LBP

After respectively use LBP algorithm and gradient LBP algorithm to extract facial features, then combine them using tandem. Because LBP and gradient LBP features have different contribution to face recognition, they need to have appropriate weights ω1, ω2, where ω1 + ω2 = 1; because gradient LBP include abundant information, giving greater weight, resulting in a weighted combined LBP and gradient LBP face feature vector.

$$X = \omega_1 \times LBP + \omega_2 \times G - LBP \tag{6}$$

4. Establishment of Face Classifiers

Let the given sample set be $\{(x_1, y_1), \cdots, (x_i, y_i), \cdots (x_n, y_n)\}$, through nonlinear mapping function $\varphi(x)$ to have the optimal separating hyperplane structure in high dimensional feature space:

$$f(x) = w \cdot \varphi(x) + b = 0 \tag{7}$$

In the Formula, w is the weight vector, b denotes threshold.

Based on structural risk minimization principle, the optimal classification plane constraint conditions are:

$$y_i \cdot (w \cdot \varphi(x_i) + b) \ge 1 \tag{8}$$

After introduction of non-negative slack variable ξ_i it becomes:

$$\begin{aligned} &\min \frac{1}{2} w \cdot w + C \sum_{i=1}^{n} \xi_i \\ &s.t. \\ &y_i (w \cdot x_i + b) \ge 1 - \xi_i, \xi_i \ge 0, i = 1, \cdots, n \end{aligned} \tag{9}$$

Where, C is the error penalty factor.

Introduce Lagrange multipliers and transfer into the dual form:

$$\min \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j (\varphi(x_i) \cdot \varphi(x_j)) + \sum_{i=1}^{n} a_i \tag{6}$$

s.t.

$$\sum_{i=1}^{n} \alpha_i y_i = 0, C \ge \alpha_i \ge 0 \tag{7}$$

After introduction of kernel function $k(x_i, x_j)$, nonlinear classification model of SVM is as follows:

$$f(x) = sign(\sum_{i,j=1}^{n} \alpha_i y_i k(x_i, x_j) + b) \tag{8}$$

SVM is a binary classifier. In terms of a variety of face categories classification, it must construct multi-classifier to conduct face recognition; this paper uses a "one to many" way to build multi-classifier, specifically shown in Figure 4.

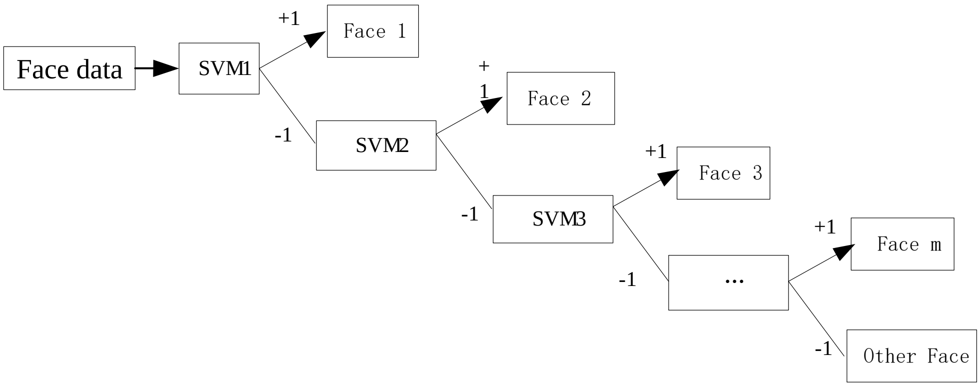

Figure 4. The Design of Face Classifier

5. Simulation

5.1. Face Data Sources

To test the effectiveness of face recognition algorithm, the author used Yale B face database, ORL face database and PIE face database for simulation experiments. Yale B face contains 38 individual images under 64 different lighting conditions, each person under different lighting conditions has five subsets, the subset 1 contains 7 images, subset 3, 4 and 5 contain 12 ,12,14,19 images respectively. The number of subsets is bigger, the illumination changes are more obvious. Yale B face image sample is shown as Figure 5.

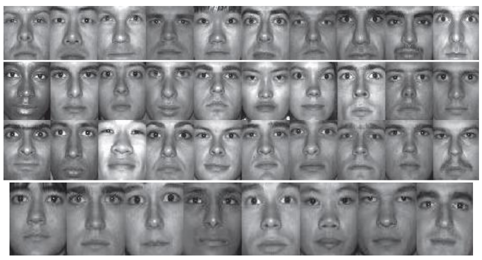

Figure 5. Yale B Face Image Sample

PIE face database is one of the most extensive face database; it contains 65 categories of face images, including a variety of illumination and facial expressions, as shown in the Figure 6, and from 1 to 21 they represent 21 images of one people.

Figure 6. PIE Face Database Sample

ORL database contains 40 categories of human face, each class has 10 images, a total of 400 images. Part of ORL face database is shown in Figure 7.

Figure 7. Part of ORL Face Database

5.2. Parameter Settings

The image is divided into 8×8 blocks. Extract LBPU2, 3DLBP and gradient LBP for each block, and then connect to form an enhanced spatial characteristics for the evaluation; support vector machine using RBF kernel function, SVM parameters C = 100, σ = 1.95 (σ denotes the width of RBF kernel function).

5.3. Results and Analysis

1. Contrast with the other LBP algorithm performance

In order to accurately evaluate the performance of this algorithm, select individually gradient LBP (G-LBP), 3DLBP and LBP of depth image for comparative experiment. G-LBP, 3DLBP and LBP performance as well as recognition results by the proposed algorithm have been shown in Figure 8. After the analysis of Figure 8, the conclusion can be obtained:

(1) With respect to the LBP algorithm, G-LBP, 3DLBP have improved the recognition rate, which is mainly due to the introduction of the facial image concentration information for better recognition results.

(2) With respect to 3DLBP algorithms, G-LBP algorithm recognition rate has been improved, which is mainly due to the G-LBP algorithm can overcome the existing defects of 3DLBP algorithm such as large length and unstable coding, which can be more accurately extract facial features, and face recognition performance is improved.

(3) With respect to the LBP algorithm, the average recognition rate of G-LBP algorithm, 3DLBP algorithm, and the proposed algorithm were increased by 8.20%, 5.10%, 2.40%, which is mainly due to the proposed algorithm combines the LBP features and gradient LBP features, and can reflect human face class information from multiple angles. It overcomes the single feature that can only represent human face one-sided, in part, or human face images cannot be fully described. The comparative results show that the proposed algorithm is a reliable face recognition algorithm with height recognition rate.

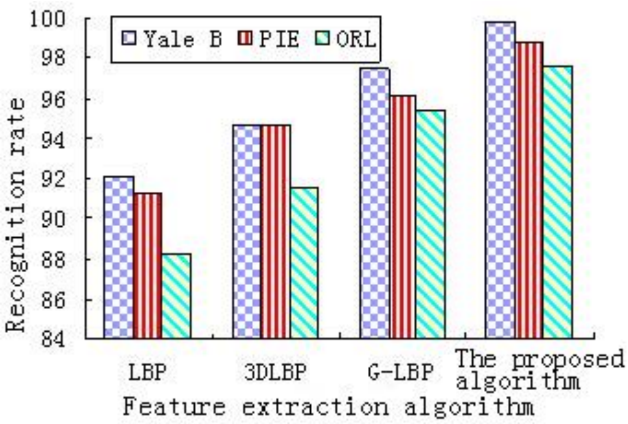

Figure 8. Performance Comparison with Other LBP Algorithm

2. Performance comparison with other classifiers

To illustrate the superiority of selecting SVM classifier as the face classifier, the author conducts comparing experiments with K nearest neighbor (KNN), RBF neural network (RBFNN) [14], BP neural network (BPNN) [15]. The results are shown in Figure 9 and it can be seen that relative to KNN, RBNN, BPNN, the proposed algorithm has highest recognition rate, while KNN has lowest recognition rate. The compared results indicate that SVM is an excellent nonlinear classification learning algorithm, which has better overcome the defects in KNN, and neural networks exist. It is helpful to build better face classifier.

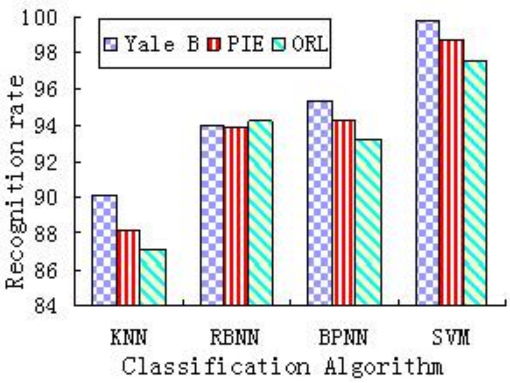

Figure 9. Recognition Performance Comparison of Different Classifiers

6. Conclusion

To improve the recognition rate, the paper proposed a face recognition algorithm integrated LBP and gradient LBP combined weighted and support vector machines, and conducted simulation experiment in the Yale B face database, PIE face database and ORL face database. The results showed that by improving local binary patterns can better extract facial features; support vector machines established a high performance face classifier, and face recognition has achieved an ideal result.

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