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Research on The Advanced Block Neighborhood Relevance Algorithm in Face Recognition

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Abstract

Concerning the face image recognition, this paper comes up with a block neighborhood relevance algorithm. Firstly, it elaborates the computational method for face image block neighborhood relevance so as to find out the smooth region and then extract features and carry out dimension reduction. Finally, the maximum margin criterion is introduced in face image improve the classification performance. Simulation experiment proves that the algorithm adopted in this paper can effectively improve the face image recognition effect.

Keywords*: Image Processing; Block Neighborhood Relevance; Maximum Margin Criterion*

1. Introduction

How to reduce the noise in face image has always been a research emphasis and at present, there is a glittering array of processing method in terms of image compression, segmentation, and filtering. Therefore, how to accurately carry out face recognition is a critical research work [1]. Scholars at home and abroad have both studied the image noise reduction.

In the course of face recognition, how to extract features is an important step and main approaches include approaches based on geometry characteristics and based on algebraic characteristic [2]. Geometrical configuration features are easily affected by shooting angle as well as illumination intensity which shall lead to unstable feature extraction [3]. Literature [4] puts forward linear discriminate analysis to analyze sparse face recognition. This approach firstly adopts linear discriminate analysis to have the subspace solution for optimal discriminant projection and then relevant data characteristics can be extracted based on the sample reflection. Literature [5] comes up with an approach to deal with face pictures taken from -45° to +45°side angle, which can obviously improve the recognition rate. Literature [6] suggests to adopting histogram equalization and uneven illumination, the distance between Mahalanobis distance metrics and picture neighborhood expectations calculated based on the mean filter and the experiment shows that the above approaches can help to create good recognition effect. Manifold-learning method mainly starts from the perspective of human perception and studies the geometric structure in high dimensional data set to construct topology embedded space which effectively solves the nonlinear problem [7-8]. What's more, it mainly constructs a local model and takes local consideration as a basis of linear space, nonlinear problem as linear problem, which is able to find out the structure in high dimensional data set and provides direct data understanding [9]. Literature [10] suggests to adopting truncated singular value decomposition to extract the demonstration and features of face image which overcomes

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the problems the old traditional method cannot deal with. Literature [11] firstly divides various noncumul parts and adopts histogram equalization to reduce noise based on local contrast stretch; then, by properly reducing low frequency DCT to remove the illumination change of face; finally, Kernel principal component analysis can be adopted to extract features to complete the face recognition.

This paper integrates the block neighborhood relevance and maximum margin criterion based on face image processing. Then, MMC function can be introduced to improve the classification performance. The simulation experiment proves that the computing method adopted in this paper can effectively eliminate the useless noise in face recognition which is a recognition approach with high identification rate as well as quick speed.

2. Introduction on the Noise of Face Recognition Features

In general, suppose the zero-mean Gaussian Attribute model for face image is

$$f_\eta(x,y) = f(x,y) + \eta(x,y) \tag{1}$$

In formula (1), (x,y) represents horizontal and vertical coordinate, $f(x,y)$ represents the original picture original and $\eta(x,y)$ represents independent identically distributed noise signal, $f_\eta(x,y)$ represents noisy image signal. Noise estimation is actually testing the noisy image difference $f_\eta(x,y)$ in original image with edge and texture. The relevance can be known by calculating the difference between global elemental area and close elemental area in certain block neighborhood and then the smooth can determined based on the neighborhood relevance. Blocks which are not closely related can be taken as references and the smooth block can be known through certain regulations. In addition, the weighted mean for smooth block can be adopted to know the overall noise of the whole picture.

3. MMC Algorithm Description

MMC is a subspace supervising method which is advanced based on LDA algorithm and changes the object function based on quotient to the object function based on difference, solving the LDA small sample problems. What's more, it can also avoid the LAD matrix inversion and reduce computational complexity [13]. The object function of MMC is

$$J = \max\left\{\sum_{i,j} p_i p_j \left(d(m_i, m_j) - tr\left(S_i\right) - tr\left(S_j\right)\right)\right\} \tag{2}$$

In Formula (2), mi is the average value of i data, pi is the prior probability and d(mi,mj) is the Euclidean distance between i and j while Si is the within-class scatter matrix.

The target in Formula (1) aims to maximize the data distance and we can have the following formula

$$J = \max tr(S_b - S_w) \tag{3}$$

In the formula Sb represents between-class scatter matrix while Sw represents within-class scatter matrix.

Suppose there are c data and the average value of data-set is m and there should be formula

$$S_b = \sum_{i=}^{c} p_i (m_i - m)(m_i - m)^T \tag{4}$$

$$S_w = \sum_{i=}^{c} p_i S_i \quad (5)$$

We introduce β to weight Sb and Sw and the object function for MMC algorithm is

$$J = \max tr(S_b - \beta S_w) \tag{6}$$

4. Improve the Block Neighborhood Relevance Algorithm

4.1. Block Neighborhood

The block information of image pixels has relevance and the different signals of close elementary area reflect the relevance and the block neighborhood relevance algorithm takes full advantage of this feature. The computing steps show as follows:

Step 1: In N *N elementary area block, the average value of one certain elemental area and neighborhood pixel difference is calculated with formula.

$$\varepsilon_i = \frac{\sum_j | f_i(x,y) - f_j(x,y) |}{n} \tag{7}$$

In the formula, ε_i is the relevance of elementary area i , j refers to the subscript index of i neighborhood while n refers to the pixel number.

Step 2: Calculate the average value of pixels correlation in the block showing in formula :

$$\varepsilon = \frac{\sum_{i=1}^{N} \varepsilon_i}{N} \tag{8}$$

In Formula (8), ε refers to the correlation degree of block neighborhood while N refers to the pixel number.

The computing method to calculate the relevance degree of block neighborhood takes the difference into consideration which can perfectly analyze the relevance among pixels so as to judge the smoothness. The smaller the relevance, the pixel gray is closer and we can know that the edge and details are fewer and the block is smooth.

Take the 4×4 blocks as an example to calculate the relevance degree of block neighborhood. For easy description, the pixel marks show in Figure 2:

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16

Figure 2. 4×4 Pixel Mark

As shown in Figure 2, mark 2, 5 and 6 is the neighbor of 1 and the relevance degree of pixel 1 is shown in Formula (9).

$$\varepsilon_1 = \frac{\sum_{j=2,5,6} | f_1(x,y) - f_j(x,y) |}{3} \tag{9}$$

In the same way, the relevance degree of pixel 6 and 16 is shown in Formula (10) and (11).

$$\varepsilon_2 = \frac{\sum_{j=2,5,7,10} | f_2(x,y) - f_j(x,y) |}{5} \tag{10}$$

$$\varepsilon_5 = \frac{\sum_{j=12,15} | f_5(x,y) - f_j(x,y) |}{8} \tag{11}$$

Therefore, there are 16 pixels. Finally, we can calculate the relevance degree of this block showing in formula

$$\varepsilon = \frac{\sum_{i=1}^{9} \varepsilon_i}{16} \tag{12}.$$

4.2. Face Characteristics Dimension Reduction and Extraction

Suppose the c sub-model for i face training sample is x_i^c (c=1,2,…,C; i=1,2,…,N), and the target for SPP to extract face image characteristics is to find out projection matrix W and we project x_i^c into low dimensional space and then $y_i^c = W^T x_i^c$, y_i^c refers to the dimension reduction result of x_i^c.

4.2.1. Maintain the Structural Relationship of Various Sub-models in One Face: The first target of SPP algorithm is to keep the structural relationship of various sub-models in one face same. Suppose the collection of sub-model c of i face sample is $X^i = [x_1^i, x_2^i, ... x_c^i]$ and the first target can be concluded in formula

$$E = \sum_{i=1}^{c} \left\| x_i^c - \sum_{l \in (-c)} a_i^{cl} x_i^l \right\|^2 \tag{13}$$

E refers to reconstruction error, a_i^{cl} refers to the coefficient reconstruction for l sub-model on c sub-model.

The reconstruction error formula of x_i^c is:

$$\varepsilon = \sum_{l \in (-c)} \sum_{m \in (-c)} a_i^{cl} a_i^{cm} G_{lm} \tag{14}$$

In formula, $G_{lm} = \left(x_i^c - x_i^l \right)^T \left(x_i^c - x_i^m \right)$

Through the least square method, the formula to calculate the reconstruction coefficient is:

$$a_i^{cl} = \frac{\sum_{m\in\{-c\}} G_{lm}^{-1}}{\sum_{p\in\{-c\}} \sum_{q\in\{-c\}} G_{pq}^{-1}} \tag{15}$$

for coefficient reconstruction and in order to keep same the structural relationship in low dimensional space we suppose the coefficient reconstruction of x_i^c is y_i^c an in order to have the low-dimensional feature of local images,

$$\varepsilon = \left\| y_i^c - \sum_{l\in(-c)} a_i^{cl} y_i^l \right\|^2 \tag{16}$$

we have to minimize the face image, namely for N image in the training sample, the object function is

$$\begin{aligned} &\min \sum_{i=1}^{N} \sum_{c=1}^{C} \left\| y_i^c - \sum_{l\in(-c)} a_i^{cl} y_i^l \right\|^2 \\ &= \min \sum_{i=1}^{N} \sum_{c=1}^{C} \left\| W^T x_i^c - \sum_{l\in(-c)} a_i^{cl} W^T x_i^l \right\|^2 \end{aligned} \tag{17}$$

suppose $P = \sum_{i=1}^{N} X_i M_i X_i^T$, the Formula (17) can be reduced to

$$\min tr\left(W^T Q W\right) \tag{18}$$

4.2.2. Maintain the Nonlinear Manifold of Sub-Models of Different Face Images: The second target is to maintain the nonlinear manifold of sub-model collection in the same position of different face images. Suppose the sub-model set for c sub-model is $X^c = [x_1^{\ c},\ x_2^{\ c},\ldots,\ x_N^{\ c}]$ and the sub-space feature is $Y^c = [y_1^{\ c},\ y_2^{\ c},\ldots,\ y_1^{\ c}]$. We can keep the neighborhood relationship to complete the second target that is to say to minimize the cost function:

$$\begin{aligned} &\min \sum_{i=1}^{N} \sum_{j=1}^{N} \left\| y_i^c - y_j^c \right\| S_{ij}^c \\ &= \min \sum_{i=1}^{N} \sum_{j=1}^{N} \left\| W^T x_i^c - W^T x_j^c \right\| S_{ij}^c \end{aligned} \tag{19}$$

In the formula, S_{ij}^c is the similarity of x_i^c and x_j^c in high dimensional space and the definition show as follows:

$$S_{ij}^c = \begin{cases} \exp\left(\dfrac{-\| x_i^c - x_j^c \|}{t}\right), x_i^c \in N(x_j^c)\ or\ x_j^c \in N(x_i^c) \\ 0, \qquad\qquad\qquad\qquad others \end{cases} \tag{20}$$

In the course of sub-graph construction, the face images of training set is divided into C sub-model set and then for all sub-model sets, the target function for nonlinear manifold is formula ,

$$\min \sum_{c=1}^{C}\sum_{i=1}^{N}\sum_{j=1}^{N} \| y_i^c - y_j^c \| S_{ij}^c$$
$$= \min \sum_{c=1}^{C}\sum_{i=1}^{N}\sum_{j=1}^{N} \| W^T x_i^c - W^T x_j^c \| S_{ij}^c \tag{21}$$
$$= \min \sum_{i=1}^{C} tr\left(W^T X^c L^c X^{c^T} W\right)$$

suppose $P = \sum_{i=1}^{C} X^c L^c X^{c^T}$ and Formula (21) to

$$\min tr\left(W^T P W\right)$$

(22)

show as follows: Finally, we integrate target Function (21) and (22) to have formula

$$\min tr\left\{W^T (P + \theta Q) W\right\} \tag{23}$$

among which, θ refers to the balance parameter and if θ≥0, relevant constraint condition should be

$$\begin{cases} W^T Z Z^T W = I \\ Z = [x_1^1, x_1^2, \ldots x_1^C, \ldots, x_N^1, \ldots x_N^C] \end{cases} \tag{24}$$

4.2.3. Set Target Function Value: This paper takes discrimination performance of feature space into consideration, and introduces the maximum margin criterion function, adopting category information, which improves the classification performance and the object function is concluded in formula .

$$\begin{cases} \arg\min\limits_{W} tr\left\{W^T \left(P + \theta Q - S_b + \beta S_w\right) W\right\} \\ s.t. \qquad W^T Z Z^T W = I \end{cases} \tag{25}$$

Lagrangian multiplier method is adopted to optimize problem and Formula (25) can be transferred into generalized eigen-decomposition formula

$$\left(P + \theta Q - S_b + \beta S_w\right) W = \lambda Z Z^T W \tag{26}$$

After decomposing the above formula, we choose d characteristics to construct mapping matrix formula.

$$W = [w_1, w_2, \ldots, w_d] \tag{27}$$

5. Simulation Experiment

5.1. Source of Face Database

In order to test the effectiveness of face recognition algorithm adopted in this paper we adopt Yale B, ORL and PIE face database to carry out simulation experiment. Yale B face includes the pictures taken for 38 people under 64 lighting conditions. Everyone has 5 subsets under different lighting condition and subset 1 has 7 pictures, subset 2, 3, 4 and 5 has 12, 12, 14, and 19pictures. The bigger the subsets, the more obvious the lighting condition is. The face image of Yale B shows in picture 5.

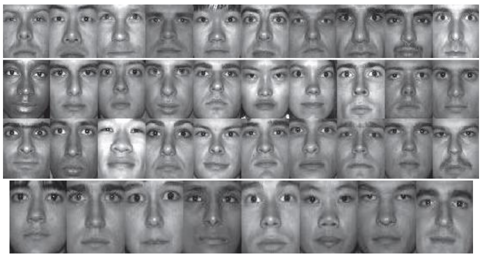

Figure 3. Yale B Database Face Sample

PIE face database is widely adopted in face recognition, which includes 65 face images, various lighting conditions and expressions showing in Figure 6 and 1 to 21 represent 21 pictures of one person.

Figure 4. PIE Database Face Sample

ORL face database has 40 type face and each of them have 10 pictures, totally 400 images. Parts of the face samples in ORL database show in Figure 7.

Figure 5. ORL Database Face Sample

5.2. Result and Analysis

In order to elaborate the superiority of the algorithm adopted in this paper, we carry out a comparison between this approach and other classic extraction methods, which are PCA, LDA and LLE. We conduct 10 simulation experiments for each algorithm and take the average value as the result and the face recognition result is showing in Figure 9. We can clearly see in Figure 6 that, comparing to face characteristics extraction, the algorithm adopted in this paper can improve the effect because it integrates deep information and LBP characteristics and the proper vector can describe the category information acquiring ideal face recognition effect.

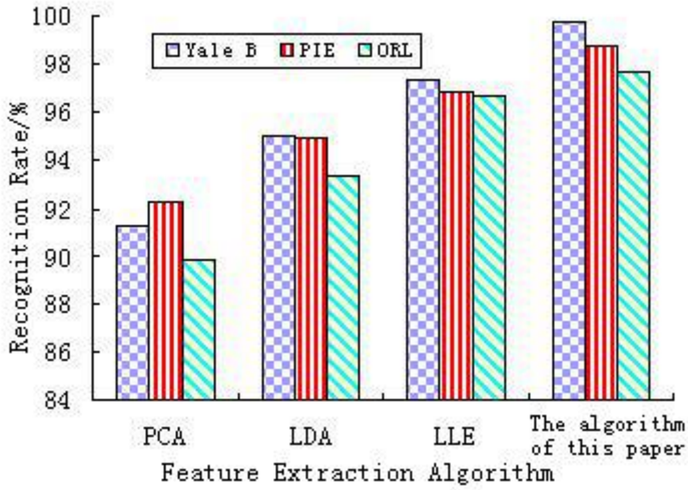

Figure 6. Comparison Between Classic Extraction Algorithms and Algorithm Adopted in This Paper

6. Conclusion

In order to improve the face recognition rate, we come up with an approach to integrate the block neighborhood relevance and Maximum Margin Criterion. What's more, simulation experiment is conducted in Yale B, PIE and ORL face database, and the result proves that local binary pattern can better extract the face characteristics and support vector machine establishes face classifier with excellent performance which can achieve ideal face recognition effect.

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