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Using the original and symmetrical face training samples to perform collaborative representation for face recognition

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ABSTRACT

More training samples are able to reveal more possible variation of the illumination, expression and poses and are consequently beneficial for correct classification. However, in real-world applications, there are usually only a limited number of available training samples. Therefore, it is hard to effectively improve the accuracy of face recognition. The symmetry of face is of great importance to face recognition. In this paper, based on the symmetry of the face, the new mirror training samples are first generate new samples. Then the original training samples and the generated symmetry training samples are, respectively, used to perform collaborative representation based classification method. Finally, the scheme of the score level fusion is adopted to integrate the original training samples and symmetrical face training samples for ultimate face recognition by assigning a larger weight to the original training samples. The experimental results show that the proposed method can classify the face with a high accuracy.

1. Introduction

Face recognition is one of the most attracting and challenging tasks in pattern recognition and real-world applications [1,2]. Over the past three decades, face recognition technology has made considerable development [3,4]. However, the recognition rate will be decrease sharply when it refers to the non-ideal imaging environments or the incorporation of users, such as variable facial expressions, gestures and illuminations. The robust face recognition remains a very challenging task.

Recently, sparse representation becomes a hot topic of pattern recognition and computer vision. Wright et al. [5] apply sparse representation to classification and exploit the sparse representation based classification (SRC) algorithm. For SRC, a test sample is represented as a sparse combination of training samples, and its sparse representation coefficient is obtained by solving the problem of sparse representation. The test sample is assigned to the class that minimizes the residual between itself and the reconstruction constructed by training samples of this class. SRC shows its effectiveness in face recognition experiments. Gao et al. [6] introduced a kernelized version of SRC. Cheng et al. [7] discussed the L1-graph for classification, Yang et al. [8] proposed a robust sparse coding method, by modeling the sparse coding as a sparsity constrained robust regression problem, and it is robust to outliers. Yang and Zhang [9] used the Gabor features for SRC with a learned Gabor occlusion dictionary to reduce the computational cost. Lai et al. [10] proposed a sparse local discriminant projections method which imposes a sparse constraint on local discriminant projections, and requires that the test sample be sparsely represented by the training samples. Though SRM can perform very well in pattern classification, it has a much high computational cost. This is indeed the obstacle to apply SRM. The main reason is that SRM must solve a L1 norm based optimization problem. In Ref. [11], Zhang et al. analyzed the working mechanism of SRC. They indicated that it is the collaborative representation, but not the L1-norm sparsity that plays the essential role for classification in SRC. Based on this, many representation based classification with least square method are proposed [12–16]. Xu et al. [13] proposed a two-phase test sample sparse representation method (TPTSSR) which makes coarse to fine classification decisions for the face samples and obtains good performances. Zhang et al. [11] proposed collaborative representation based classification with regularized least square (CRC_RLS), and they indicated that the CRC_RLS has very competitive classification results, while it has significantly less complexity than SRC. Shi et al. [12] also illustrated that the sparity representation methods with L2 norm outperforms the well-know sparity representation with L1 norm in classification accuracy.

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It has proved that more training samples are able to reveal more possible variation of the lighting, expression, pose and are consequently beneficial for correct classification. However, we don't have so many images to be taken as training samples for each subject in reality. This is mainly because a face recognition is usually small sample size problem (SSS). Non-sufficient training samples indeed have become one bottleneck of face recognition [17–20]. In order to obtain better face recognition result, the literatures have proposed to synthesize new samples from the true face images. For example, Liu et al. [21] used the improved quotient image method to generated one new image of each subject under the same lighting conditions with an input image. Thina et al. [22] exploited simple geometric transformations to synthesize virtual samples. Jung et al. [23] adopted the noise to synthesize new face samples. The multiple virtual views images of a person under different poses and illumination from a single face image were synthesized [24]. Symmetry is an important feature in natural scenes that attracts our attention and seems to guide the process of recognition. We note that the face has a symmetrical structure. Not only the facial structure but also the facial expression is symmetry. This has motivated many studies of symmetry and associated techniques that might be applied to image processing. For example, the symmetry property of the human face is very useful to quickly locate the candidate faces in face detection [25,26].

In this paper, we propose to use the symmetry of the face to generate new training samples and design a collaborative representation based classification method (CRC). According to the symmetrical structure of face, the left/right mirror images are first generated for each training sample. Then, the original and new generated training samples are, respectively, used to perform collaborative representation based classification method. Finally, the score level fusion is adopted to calculate the ultimate score according to the scores of the original test samples and its symmetrical test samples.

This paper is organized as follows: Section 2 introduces the collaborative representation based classification method (CRC). In Section 3, the proposed method is presented. Section 5 presents some experiment results and discussion. The final section gives our conclusions.

2. Collaborative representation based classification method (CRC)

Assume that each image is of the size $w \times h$, and it can be viewed as a point in the space R^m with $m = w \times h$, Suppose that we have N training samples for c classes and each class includes n_k training samples, $A_k = [a_{k,1}, \ldots, a_{k,n_k}] \in R^{m \times n_k}$, where m is the dimension of samples. Any test sample $y \in R^m$ from the kth class can be approximately represented as the linear combination of all training samples:

$$y = \alpha_{1,1}x_{1,1} + \alpha_{1,2}x_{1,2} + \cdots + \alpha_{c,n_c}x_{c,n_c} \tag{1}$$

where $x_{i,j} \in R$, $i = 1, 2, \ldots, c$, $j = 1, 2, \ldots, n_c$. Assume $X_i = \left[x_{i,1}, x_{i,2}, \ldots, x_{i,n_i}\right]$. Define a new matrix A for the entire training set as the concatenation of the N training samples of all c objects:

$$\begin{aligned} A &= [A_1, A_2, \ldots, A_c] \\ &= \left[a_{1,1}, a_{1,2}, \ldots, a_{c,n_c}\right] \in R^{m \times n} \end{aligned} \tag{2}$$

where $n = n_1 + n_2 + \cdots + n_c$. Then the linear representation of y can be rewritten in terms of all training samples as

$$y = AX \tag{3}$$

where $X = [X_1, X_2, \ldots, X_c]$.

In order to collaboratively represent the test sample y using all training samples with low computational burden, the objective function is

$$\left(\hat{X}\right) = argmin_X \left\{ \left\| y - A \times X \right\|_2^2 + \lambda \left\| X \right\|_2^2 \right\} \tag{4}$$

where λ is the regularization parameter. The effect of the regularization term is as follows. First, it makes the least square solution stable. Second, it introduces a certain amount of "sparsity" to the solution $\hat{X}$. X should be computed using Eq. (2).

$$\hat{X} = \left(A^T A + \lambda I\right)^{-1} A^T y \tag{5}$$

where I denote the identity matrix.we calculate the sum of the contribution to represent the test sample from each class and exploit the sum to classify the test sample. Namely, we use the following equation to evaluate the contribution, of the training samples of the i th class, in representing the test representation.

$$con_i = \frac{\left\| y - A_i \times \widehat{X_i} \right\|_2}{\left\| \widehat{X_i} \right\|_2} \tag{6}$$

A smaller deviation con_i means a greater contribution to representing the test sample. If $h = arg \min_i con_i$, we will assign test sample y into the h th class.

The main steps of the CRC are as follows.

Step 1. Let y denote the test sample. Use $y = \left(y/||y||\right)$ and $a_{k,i} = \left(a_{k,i}/||a_{k,i}||\right)$ $(1 \le i \le n)$ to convert the test sample and training samples into unit vectors.

Step 2. Solve the L2-minimization problem:

$$\widehat{X} = arg\min \|x\|_1 \quad \text{subject to} \quad y = AX \tag{7}$$

Step 3. Compute the regularized residuals using Eq. (6).

Step 4. Output the identity of y as

$$\text{Identity}(y) = arg\min_i \left\{ con_i \right\} \tag{8}$$

3. The proposed method

The main idea of the proposed method is generally described as four steps. The first step generates the corresponding symmetrical training samples for every training sample. The second and third steps respectively use the original and generated new samples to perform collaborative representation based classification method (CRC). The fourth step get the ultimate classification result according to the weighted level fusion scores which is computed by combining the scores obtained using the second and third steps.

Step 1. Every original training sample is mirrored to generate two symmetrical training samples. Assume $z_i \in R^{p \times q}$ to be a training sample from the ith class, and the corresponding generated symmetrical face images of the training image z_i are, respectively, denoted by z_i^1 and z_i^2. Based on the face center of the image z_i, the left face image z_i^L and right face image z_i^R are first obtained.

$$\begin{aligned} z_i^L &= z_i \left[:, \quad 1 : \left(\frac{q}{2}\right)\right] \\ z_i^R &= z_i \left[:, \quad 1 : \left(\frac{q}{2}\right) + 1 : q\right] \end{aligned} \tag{9}$$

Then the two half face images are, respectively, mirrored, and their mirror images are produced, denoted by $z_i^{L'}, z_i^{R'}$,

$$\begin{aligned} z_i^{L'}(m, n) &= z_i^L\left(m, \left(\frac{q}{2}\right) - n + 1\right) \\ z_i^{R'}(m, n) &= z_i^R\left(m, \left(\frac{q}{2}\right) - n + 1\right) \end{aligned} \tag{10}$$