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REGULARIZED CLUSTERING BASED DOUBLE MANIFOLD DISCRIMINANT ANALYSIS FOR LOW-RESOLUTION FACE RECOGNITION

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Abstract. *In this paper, we propose a regularized clustering-based double manifold discriminant analysis (RC-DMDA) method for low-resolution face recognition with single sample per person (SSPP). The proposed method makes use of regularized clustering to reduce the number of features via making the feature coefficients close to zero so as to dodge the potential overfitting risk caused by single sample per person. Since the conventional algorithms for low-resolution face recognition suffer from unpleasant robustness arisen by the global information, the proposed method utilizes a double manifold discriminant learning algorithm, in which both local features and global features are employed to reduce the redundant information existing in the training samples. To evaluate the performance of the proposed method, high-resolution face images from benchmark datasets are down-sampled to low-resolution ones on account of the lack of test samples, and moreover only one image for each category is down-sampled. Furthermore, five sets of training data with different numbers of pixels are used for evaluating the recognition accuracy under diverse pixel conditions. Extensive experiments on various datasets validate the effectiveness of the proposed method by comparing with the state-of-the-art methods.*
Keywords: Face recognition, Single sample, Low-resolution, Manifold discriminant method

1. **Introduction.** Recent years have witnessed great progress made in face recognition [1,2], and the recognition accuracy of several methods has exceeded the resolving capability of human eyes. Most of existing algorithms for the face recognition require training samples more than three images per person [3-5], while it is actually hard to obtain multiple high-resolution training samples per person from different view angles and with diverse expressions [6]. Moreover, the proliferation of modern shooting equipment such as surveillance cameras enables photographic distances to be increased, resulting in a very low proportion of human face in an entire photographic image and causes a decrease in facial image resolution. Low-resolution face recognition with SSPP becomes a great challenge for practical applications of current algorithms such as law enforcement. Thus working with low-resolution face images attracts more attention in the field of face recognition with SSPP [7-9].

To realize the low-resolution face recognition with SSPP, many algorithms have been given in the literature, which can be mainly classified into two categories. One solution to this issue is to leverage the power of super-resolution (SR) techniques. Such techniques aim to reconstruct high-resolution (HR) ones from low-resolution (LR) face images in the dataset and then measure the similarity between the HR and LR image patches [10] using Euclidian distance or Cosine distance. On the basis of super-resolution reconstruction, various algorithms are utilized to improve the matching degree between HR and LR

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images. A representative way for such techniques is SR method with Tikhonov regularized neighbor representation for low-resolution face recognition [11], which can alleviate the impact of noise coefficients. To facilitate the extraction of the effective information, Huang et al. [12] propose a method for enhancement of the corresponding relationship between high-resolution and low-resolution images by using canonical correlation analysis (CCA). Compared with other type of algorithms for face recognition, these SR methods generally achieve better visual effect of final images in expense of higher computational complexity at the same recognition rate.

To improve the recognition accuracy in an efficient way, patch-based algorithms [13] are presented for the LR face recognition, in which an image is first segmented into N patches before face recognition. Pang et al. [14] propose a patch-based method using a robust heterogeneous discriminative analysis (RHDA). However, by this way, both LR and HR images restored from LR images cannot be recognized efficaciously. In addition, several approaches based on a block sparse matrix have appeared in the literature, such as block-based Fisher linear discriminant analysis (Block FLDA) [15] and low-rank regularized representation with a block-sparse structure (LRR-BSS) [16]. Although these attempts have addressed the LR face recognition issue to some extent, they endure performance degradation. Besides, we note that conventional methods (such as KNN, and LBP) are also applied to solving this problem on the basis of patch-based algorithm [17].

Motivated by these observations, we propose a double manifold learning method based on regularized clustering, exploiting the strengths of local features and manifold learning. Compared with the existing algorithms, the main advantages of this paper are as the following. 1) Segment training images at both global and local levels to reduce feature dimensions. 2) Regularized clustering analysis and double manifold learning are combined to alleviate the overfitting problem. 3) Compared with the state-of-the-art algorithms, the maximum recognition accuracy of RC-DMDA can reach 84.58%.

The remainder of this paper is organized as follows. Second 2 elaborates the proposed method in detail. Section 3 provides the experimental results. Finally, we conclude the paper and provide future research directions in Section 4.

2. **Proposed Algorithm.**

The core thought of the proposed RC-DMDA method is to employ the regularized clustering analysis for obtaining optimal clustering result and double manifold learning strategy for dimension reduction and feature extraction, whose purpose is to improve directly the recognition accuracy rather than visual effects of target images pursued by conventional algorithms and extend its potential applications.

2.1. **Regularized clustering analysis.**

A dataset consisting of N face images is produced firstly, where $N = [h_1, h_2, \ldots, h_n] \in H^{M\times C}$, H denotes training datasets composed of HR images and h_i is the ith face image in the dataset, M and C represent the dimension of image features and the classification of the datasets, respectively. The key idea of the proposed regularized clustering analysis method is illustrated in Figure 1. We can observe from Figure 1 that HR images in the dataset are initially classified into several classes based upon their distances. Moreover, LR images can be obtained by down sampling HR ones in the dataset. HR and LR images are pre-classified by regularized clustering algorithm on account of only one HR face image per person enrolled in the dataset. The distance between within-class images is reduced along with increased number of iterations.

Next, we construct a matrix V, which is the similarity matrix of H, and its corresponding Laplace transform matrix can be expressed as:

$$L_v = \frac{D_v - \left(V^T + V\right)}{n} \tag{1}$$

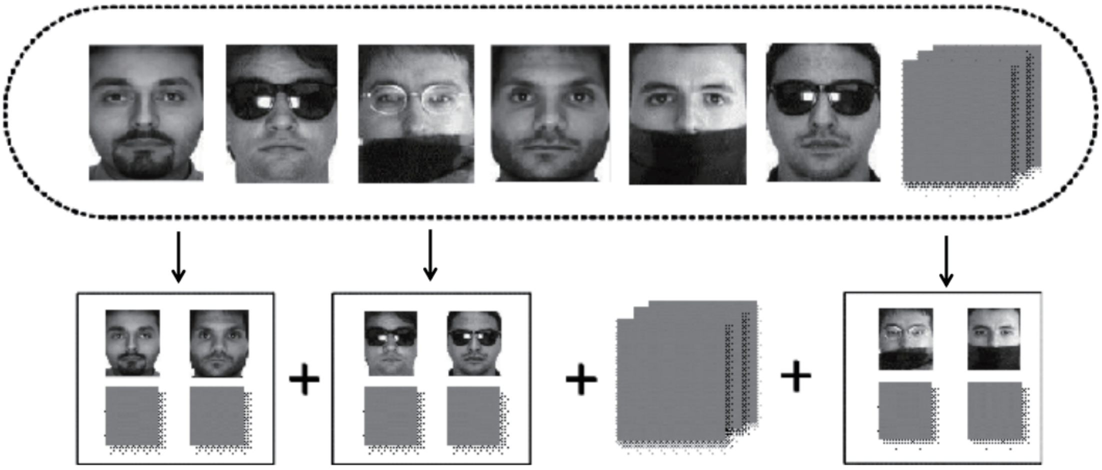

FIGURE 1. A schematic diagram of the proposed regularized clustering analysis method

On this basis, the constraint item is introduced into the objective function, the regularization term is added to the objective function, and the model is expressed as:

$$j = \frac{\left[\sum_{i=0}^{n} \left|h_n(x_i) - h_n(x_j)\right|^2 V_{ij} + \lambda \sum_{i=1}^{n} V_{ij}^2\right]}{n} \tag{2}$$

H is a non-negative matrix subjective to the non-negative constraint. Such regularized clustering algorithm is able to simplify the model of feature extraction by adding a constraint term, which enables the feature function more suitable for LR face image recognition.

In addition, K-means regularized clustering algorithm assigns the images with similar structures grouped to one category. In order to reduce the computational complexity of the proposed method, K is set to 20 based upon prior experience.

The images with different structures and variant features are relatively far away in the subspace. When the samples belong to the same category, the final output of matrix will be larger. K-means regularized clustering algorithm participates N images into K clusters according to the image structure similarity. The main steps of K-means regularized clustering algorithm are as the following. First, K clustering centers denoted by $C = [C_1, C_2, \ldots, C_k]$ $(k \leq n)$ are initialized. Second, a matrix consisting of intra- and inter-class samples is calculated by

$$\max \frac{\beta T_b^{class} + (1-\beta) T_b^{cluster}}{\alpha T_w^{class} + (1-\alpha) T_w^{cluster}} = \max C = \max \frac{(P_H, P_L)}{(P_H, P_L)} \tag{3}$$

α and β are the coefficients of the regularized term. Finally, the Euclidean distance from each sample to every clustering center is measured by

$$dis(h_i, C_j) = \sqrt{\sum_{t=1}^{n} (h_{it} - C_{jt})^2} \tag{4}$$

where C_j denotes the jth clustering center, and t represents the tth feature $(t < m)$.

The dimension (m) of feature vectors of the LR face datasets is usually much smaller than the feature dimension (M) of HR ones. In other words, the number of effective geometric features and contour features extracted from LR samples is reduced significantly. As a result, it is impossible to compare the similarity between the HR image and the LR image in a direct way. To solve the problem of dimension mismatch between HR and LR images, we prefer to adopt double manifold discriminant analysis method. This approach contributes to follow-up double manifold learning and dimensionality reduction.

2.2. **Image segmentation.** All the samples in the datasets are first segmented into S patches to efficiently construct local manifold. The central pixel is selected as a threshold, which is compared with its eight adjacent pixels. In this way, the texture features of the whole face can be extracted from HR and LR samples. Compared with the method of extracting texture features directly from the face images, the proposed method enhances its robustness by combining both geometric and structural features of HR and LR samples.

2.3. **Double manifold learning.** The proposed RC-DMDA method based on RHDA [14] is shown in Figure 2. We can see from Figure 2 that the main purpose of double manifold learning approach is to construct two manifolds: one shown in the first row aims to extract local features from face images in the dataset, and the other shown in the second row is used to explore the global features in the single image per person. In the RC-DMDA approach, the contour features of all face images are extracted from HR and LR datasets at the global level, and then the first manifold is constructed. According to the neighbor relationship obtained at segmentation stage, we can calculate the neighborhood reconstruction coefficients of face samples and construct a linear relationship between face samples as

$$\min_{w_1,w_2,\dots,w_n} \sum_{i=1}^{n} \left\| x_i - \sum_j w_{ij} x_j \right\|_2^2 \tag{5}$$

$$\text{s.t.} \ \sum_j w_{ij} = 1 \tag{6}$$

FIGURE 2. The schematic diagram of double manifold learning

In this process, we suppress the similarity of the patches from different classes, while the similarity of inter-class patches is enhanced for all images by

$$\min \Phi^w(N+n) = \sum_i \left\| (N+n)_i W^T - \sum_j S_{ij}^w W^T (N+n)_i \right\|^2 \tag{7}$$

$$\max \Phi^b(N+n) = \sum_{i,j} \left\| (N+n)_i W^T - (N+n)_j W^T \right\|^2 S_{ij}^b \tag{8}$$

The local geometric features are then extracted from the same position of all samples in the datasets to construct the second manifold. Finally, the similarity between two manifolds and face images is obtained by voting.

3. **Experimental Results.** The experiments are carried out on the Intel i5-3230M, 2.6GHz, RAM 8GB personal computer using MATLAB R2017b. For the regularized clustering process, a large number of researches reported reveal that the clustering effect of K-means algorithm is better with $K = 20$, so we still set K to 20 in our experiments.

3.1. **Evaluation on FERET database.** Performance evaluation provided in this section is conducted on FERET [18] face dataset. The FERET contains 14051 face images corresponding to 1564 individuals who are distinct across ethnicity, gender, and age. In these experiments, a subset from FERET database composed of 100 subjects is used to make performance comparison between the proposed method and state-of-the-art approaches for LR face recognition. There are 100 groups (each of groups corresponds to one person) in the chosen subset, and moreover only one HR image including at least one variation is selected from each of groups. And we test LR face samples on five different resolutions, i.e., 8×8, 10×10, 12×12, 14×14 and 16×16 pixels. Figure 3 illustrates six HR face images and their corresponding LR samples in FERET subset. HR face images are used to train the proposed model, and the rest LR ones are used as the probe images.

Figure 3. The illustration of HR and LR images

In order to compare the proposed RC-DMDA with similar approaches on recognition performance, we conduct several experiments on LR face images of five resolutions, 8×8, 10×10, 12×12, 14×14 and 16×16 pixels, and the experimental results are shown in Table 1. As previous researches, both PCA and PCA+SVM methods are tested on the HR images. Moreover, these probe images used in our experiment have no occlusion and variations of light, expression and pose. Table 1 illustrates that the proposed RC-DMDA approach achieves recognition performance better than others in case of LR probe images. Especially, as can be observed, when the resolution of the probe images is quite low, namely 8×8 pixels, the proposed RC-DMDA achieves the highest recognition rate among all the methods. The strong record is benefiting from the effectiveness of regularization algorithm for a single face matching application. It can be also derived from Table 1 that the proposed method possesses strong robustness since its recognition rate obtained on

Table 1. Comparison of recognition accuracy (%) on FERET dataset with five methods

Methods	8×8	10×10	12×12	14×14	16×16	HR (80×80)
SDA [19]	68.75	72.08	71.77	71.98	72.08	–
PCA [20]	–	–	–	–	–	72.16
CMFA [21]	72.08	75.40	75.40	75.60	75.68	–
PCA+SVM [22]	–	–	–	–	–	82.50
RC-DMDA	80.65	80.73	81.65	81.65	84.58	–

probe images with varied resolutions from 8×8 to 16×16 pixels decreases by 3.93%. This may attribute to exploiting both global and local features to enhance the error tolerance of the algorithm. Compared to them, our method is more suitable to recognize quite LR face images due to its reliable recognition rates.

3.2. **Evaluation on LFW database.** In the real world, apart from lower resolutions, there are other factors such as illumination and dark background. In order to measure recognition performance of RC-DMDA under unconstrained circumstances, a number of experiments are conducted on LFW [23] dataset with the same experimental setting as before. The LFW consists of the face images of 5749 subjects taken under unconstrained setting. The complicated surroundings of image capture and inaccurate alignment of faces make LFW dataset more challenging for LR face recognition.

In these experiments, a subset is formed with 158 subjects from LFW dataset, and only one image is selected for each subject. Those images are used in training process. Next the resolutions of selected sample images are resized to 8×8, 12×12 and 16×16 pixels, and our task on this dataset aims to recognize LR face images with these three resolutions. The experimental results are illustrated in Table 2.

Table 2. The recognition accuracy (%) on LFW dataset

Methods	8×8	12×12	16×16
SDA [19]	4.94	6.96	7.85
CLPM [7]	4.10	6.58	7.47
CMFA [21]	9.49	10.38	10.89
RC-DMDA	14.50	17.08	18.71

As can be seen from Table 2, the recognition accuracy obtained from all the methods is not high due to the fact that LR probe images captured by uncontrolled setting contain challenging facial variations. Nevertheless, compared with other algorithms, the proposed RC-DMDA achieves better recognition performance due to its higher average recognition accuracy of 16.76%. Moreover, the recognition rates obtained by our method on the probe images with low resolutions, 8×8 and 16×16 pixels, are 14.50% and 18.71%, which are higher than others.

3.3. **Component analysis.** Manifold analysis is mainly applied to HR face recognition, focusing on global features rather than local ones. However, to achieve good results for LR face recognition, the proposed RC-DMDA method adopts double manifold learning based upon cluster regularization. In order to verify the effectiveness of double manifold model used in our method, we conducted several experiments with single and double manifold models. The setting of parameters and the dataset in this test is the same as those in the previous experiments.

The experimental results on FERET dataset with five different resolutions are shown in Figure 4. As it is shown, RC-DMDA without manifold of local features achieves inferior

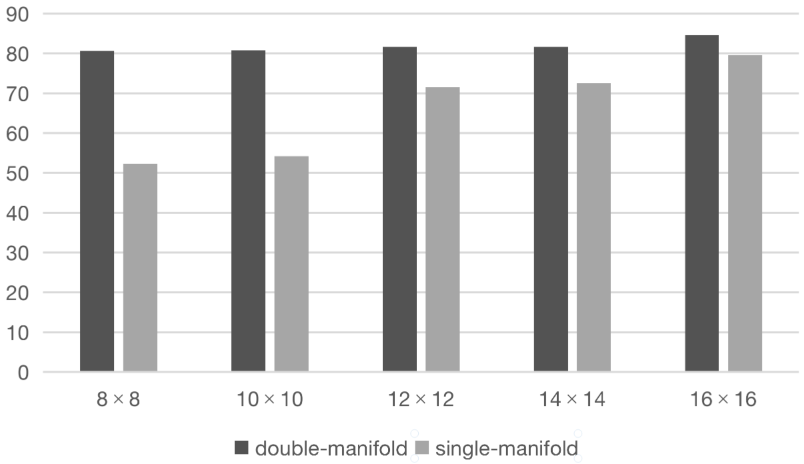

Figure 4. Recognition results (%) on FERET dataset with five different resolutions

results. When the image resolution is 8×8, the recognition rate decreases from 80.65% to 52.50%, and the difference between these experimental results is the biggest. Moreover, the difference of recognition accuracy gradually becomes small along with the increased resolutions. When the image resolution is greater than 14×14 pixels, the D-value of recognition rate is not over 5%. It can be derived from Figure 4 that the proposed double manifold method can obtain more effective information than single-manifold one in the case of quite LR face images, thus significantly improving the recognition accuracy.

4. **Conclusion.** This paper presents a double manifold discriminant analysis method based upon regularized clustering, namely RC-DMDA, to address LR face recognition problem in the case of SSPP. The proposed approach makes use of regularized clustering framework to alleviate the overfitting problem caused by SSPP. Moreover, the double manifold learning scheme is able to not only extract both global and local features from LR face images but also decrease the dimensions of features used for face recognition, which contributes to improving the robustness of the proposed RC-DMDA to some extent. We evaluate the proposed method on FERET dataset and LFW dataset, and the experimental results reveal the proposed RC-DMDA method outperforms those comparative approaches in terms of recognition rates. For future work, we are interested in reducing the training length of RC-DMDA. Moreover, how to improve the SSPP recognition accuracy with complex dataset appears to be another interesting direction of future work.

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