LOCAL CONSISTENCY PRESERVED COUPLED MAPPINGS FOR LOW-RESOLUTION FACE RECOGNITION

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ABSTRACT

Existing face recognition systems can achieve high recognition rates in the well-controlled environment. However, when the resolution of the test images is lower than that of the gallery images, the performance degrades seriously. Traditional two-step solutions (first adopting super-resolution (SR) method, and then performing the recognition phase) mainly focus on visual enhancement, rather than classification. In this paper, we utilize Local Consistency Preserved Coupled Mappings (LCPCM-I) to project the face images with different resolutions onto a new common space for recognition based on coupled mappings (CM). To achieve better results, we incorporate discriminant information with LCPCM (LCPCM-II). The experimental results on FERET database verify the effectiveness of our proposed method.

Index Terms— Face recognition, low-resolution, super-resolution, local consistency preserved couple mapping.

1. INTRODUCTION

A great number of achievements have been made in the area of automatic face recognition during the last decades, especially in well-controlled environment. However, it often happens in practical applications that the resolution of the test face images is not as high as that of the gallery face images , which degrades the performance of face recognition system severely.

Conventional methods solve this problem by first applying super-resolution (SR) to improve the resolution of input low-resolution face images followed by the procedure of recognition. There are many types of SR methods, among which learning-based SR methods are proved to perform better. Freeman et al. [1] learnt a Markov Random Field from training images to predict target HR image with MAP estimation. Inspired by LLE [2], Chang et al. [3] reconstructed HR image from its spatial neighbors. Yang et al. [4] proposed a method based on sparse representation which gets outstanding performance. However, these SR methods themselves aim at the visual enhancement, rather than at the recognition. Moreover, they are often complicated and time-consuming.

Recently, some methods have been proposed to avoid explicit SR for face recognition. Gunturk et al. [5] transferred SR reconstruction from pixel domain to eigenface-domain. Hennings-Yeomans et al. [6] [7] proposed a joint object function that integrates the aims of SR and face recognition simultaneously. B. Li [8] performed low-resolution (LR) face recognition via couple locality preserving mapping (CLPM) based on coupled mappings (CM). The CLPM brought in a penalty weighting matrix to preserve the local relationship in the original feature spaces, whose formulation was like [9] [10]. Ren et al. [11] developed a couple kernel embedding method to map face images with different resolutions onto an infinite-dimensional and nonlinear space instead of linear projection subspace via kernel method. These methods emphasize on the object of recognition rather than just reconstruction and therefore present a better performance. However, most of these algorithms discard the sample labels which are important for classification.

In this paper, we propose to employ Local Consistency Preserved Coupled Mapping (LCPCM-I) to project the faces with different resolutions onto a new common space for low-resolution face recognition based on CM. Different from [8] [11], the objective function we proposed considers not only the local relationship between HR and LR images, but also that among HR images and that among LR images, which is called local consistency constraint (LCC). Furthermore, we draw the sample labels into the penalty weighting matrix to take into count the discriminant information for classification. Compared with LCPCM-I, we named LCPCM with classification information LCPCM-II.

The remainder of this paper is organized as follows. Section II describes the problem formulation of low-resolution face recognition and coupled mappings. Our proposed methods are discussed in Section III. Section IV provides experimental results on FERET database. Finally, we conclude this paper in Section V.

2. LOW-RESOLUTION FACE RECOGNITION BASED ON CM

In the task of low-resolution face recognition, we expect for a proper distance measure between a LR image $\mathbf{l}_i$ and a HR image $\mathbf{h}_j$, i.e., $d_{ij} = \text{dist}(\mathbf{l}_i, \mathbf{h}_j)$. Here, $\mathbf{l}_i \in \mathbb{R}^m, i = 1, 2, \ldots, N_p$ and $\mathbf{h}_j \in \mathbb{R}^M, j = 1, 2, \ldots, N_g$, represent the m-dimension feature vectors of LR images in the probe set and M-dimension ($m < M$) feature vectors of HR images in the gallery set. Due to the mismatch of dimension between LR images and HR images, conventional distance measures can not be calculated directly. To solve this problem, explicit SR methods attempt to establish a mapping, $f_{SR} : \mathbb{R}^m \mapsto \mathbb{R}^M$, to ensure the match of dimension of images with different resolutions. Then, the distance measure can be calculated as

$$d_{ij} = \text{dist}(f_{SR}(\mathbf{l}_i), \mathbf{h}_j). \quad (1)$$

Different from explicit SR methods, CM method is intended to find two mappings, $f_L : \mathbb{R}^m \mapsto \mathbb{R}^d$ for LR images and $f_H : \mathbb{R}^M \mapsto \mathbb{R}^d$ for HR ones, to obtain the consistency of dimensionality. Then, the distance measure can be calculated as

$$d_{ij} = \text{dist}(f_L(\mathbf{l}_i), f_H(\mathbf{h}_j)). \quad (2)$$

Here, we define $f_L(\mathbf{l}) = \mathbf{P}_L^T\mathbf{l}$ and $f_H(\mathbf{h}) = \mathbf{P}_H^T\mathbf{h}$ are linear mappings, respectively, where $\mathbf{P}_L$ and $\mathbf{P}_H$ are two projection matrices with size of $m \times d$ and $M \times d$. To obtain the two projection matrices, CMs method minimizes the objective function

$$\mathcal{J}_{CM}(\mathbf{P}_L, \mathbf{P}_H) = \sum_{i=1}^{N_t} \|\mathbf{P}_L^T\mathbf{l}_i - \mathbf{P}_H^T\mathbf{h}_i\|^2. \quad (3)$$

where N_t indicates the number of the training images. The above objective function implies the projection of each LR image and corresponding HR ones should be as close as possible in the new common subspace. Next, we denote the original LR and HR feature spaces in the training set as $\mathbf{L} = [\mathbf{l}_1, \mathbf{l}_2, \ldots, \mathbf{l}_{N_t}]$ and $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_{N_t}]$, Eq. (3) can be reformulated as

$$\mathcal{J}_{CM}(\mathbf{P}_L, \mathbf{P}_H) = \text{tr}(\|\mathbf{P}_L^T\mathbf{L} - \mathbf{P}_H^T\mathbf{H}\|^2), \quad (4)$$

where $\text{tr}(\cdot)$ is the matrix trace operator. Furthermore, let $\mathbf{P} = \begin{bmatrix} \mathbf{P}_L \\ \mathbf{P}_H \end{bmatrix}$, $\mathbf{Z} = \begin{bmatrix} \mathbf{L} & \mathbf{0} \\ \mathbf{0} & \mathbf{H} \end{bmatrix}$ and $\mathbf{A} = \begin{bmatrix} \mathbf{L} & \mathbf{0} \\ \mathbf{0} & \mathbf{H} \end{bmatrix}$. The objective function can be rewritten as

$$\mathcal{J}_{CM}(\mathbf{P}_L, \mathbf{P}_H) = \text{tr}(\mathbf{P}^T\mathbf{Z}\mathbf{A}\mathbf{Z}^T\mathbf{P}). \quad (5)$$

$\mathbf{P}_L$ and $\mathbf{P}_H$ can be obtained by minimizing Eq. (5). Optimization solution can be acquired referring to [8].

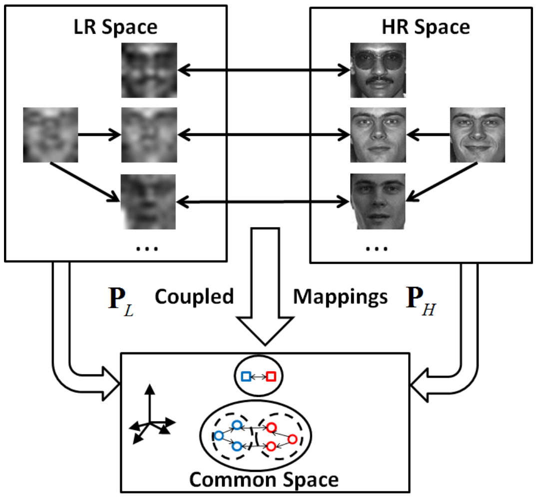

Fig. 1. Illustration of our methods via LCPCM.

3. PROPOSED METHODS

3.1. Local Consistency Preserved Coupled Mappings (LCPCM-I)

The above CM method obtains the projection in the principle that the distance measure of each LR and the corresponding HR images in the projected common subspace should be as close as possible. It does not take the local relationship of LR and HR separately into consideration, specially when there are several samples with the same labels.

Based on CM, we take one more assumption into consideration that the LR images and HR images can preserve their own local relationship separately (Illustrated in Fig. 1). Eq. (3) is developed to the following objective function.

$$\mathcal{J}(\mathbf{P}_L, \mathbf{P}_H) = \mathcal{J}_{CM}(\mathbf{P}_L, \mathbf{P}_H) + \mathcal{J}_L(\mathbf{P}_L, \mathbf{P}_L) + \mathcal{J}_H(\mathbf{P}_H, \mathbf{P}_H) \quad (6)$$

where

$$\mathcal{J}_L(\mathbf{P}_L, \mathbf{P}_L) = \sum_{i=1}^{N_t}\sum_{j=1}^{N_t} \|\mathbf{P}_L^T\mathbf{l}_i - \mathbf{P}_L^T\mathbf{l}_j\|^2 w_{ij}, \quad (7)$$

and

$$\mathcal{J}_H(\mathbf{P}_H, \mathbf{P}_H) = \sum_{i=1}^{N_t}\sum_{j=1}^{N_t} \|\mathbf{P}_H^T\mathbf{h}_i - \mathbf{P}_H^T\mathbf{h}_j\|^2 w_{ij}. \quad (8)$$

The above two formulations of Eq. (7) and Eq. (8) are inspired by the work of [9] [10]. They build a graph incorporating local relationship and are designed to minimize the weighted Euclidean distance. The heat kernel is adopted as the penalty weighting matrix $\mathbf{W} = \{w_{ij}\}$ [8] as follows:

$$w_{ij} = \begin{cases} \exp\left(-\frac{\|\mathbf{h}_i - \mathbf{h}_j\|^2}{\sigma^2}\right) & j \in N_k(i) \\ 0 & \text{otherwise} \end{cases}, \quad (9)$$

where $\sigma = \alpha \sum_{i,j} (\|\mathbf{h}_i - \mathbf{h}_j\|^2)/N_t$, and $N_k(i)$ contains the indices of k nearest neighbors of sample i.

Let diagonal matrices $\mathbf{E}^L = \{e_{ii}\} = \sum_j w_{ij}$, $\mathbf{E}^H = \{e_{jj}\} = \sum_i w_{ij}$ and

$$\mathbf{C}_1 = \mathbf{E}^L + \mathbf{E}^H - \mathbf{W} - \mathbf{W}^T + \mathbf{I}, \tag{10}$$

$$\mathbf{C}_2 = \mathbf{E}^L + \mathbf{E}^H - \mathbf{W} - \mathbf{W}^T + \mathbf{I}, \tag{11}$$

and

$$\mathbf{C} = \begin{bmatrix} \mathbf{C}_1 & -\mathbf{I} \\ -\mathbf{I} & \mathbf{C}_2 \end{bmatrix}, \tag{12}$$

Eq. (6) is reformulated as

$$\mathcal{J}(\mathbf{P}_L, \mathbf{P}_H) = \mathrm{tr}(\mathbf{P}^T \mathbf{Z} \mathbf{C} \mathbf{Z}^T \mathbf{P}). \tag{13}$$

Therefore we can solve the following optimization problem by adding the constraints as

$$\begin{aligned} \arg\min_{\mathbf{P}_L, \mathbf{P}_H} \mathcal{J}(\mathbf{P}_L, \mathbf{P}_H) \quad \text{s.t.} \quad & \mathbf{P}^T \mathbf{Z} \mathbf{Z}^T \mathbf{P} = \mathbf{I} \\ & \mathbf{P}^T \mathbf{Z} \mathbf{1} = \mathbf{0}, \end{aligned} \tag{14}$$

where $\mathbf{1}$ and $\mathbf{0}$ are the vectors of ones and zeroes respectively. Eq. (14) can be solved as a generalized eigen-problem.

Let $\mathbf{M} = \mathbf{Z}\mathbf{A}\mathbf{Z}^T$ and $\mathbf{N} = \mathbf{Z}\mathbf{Z}^T$, the solution to the optimization problem Eq. (14) can be obtained by finding the eigenvectors with respect to the second to $(d+1)$ (d is the dimension of the common space) smallest eigenvalues in the following equation.

$$\mathbf{M}\mathbf{p} = \lambda \mathbf{N}\mathbf{p} \tag{15}$$

where $\mathbf{p}$ is the eigenvector with respect to the eigenvalue λ.

3.2. LCPCM with Sample Labels (LCPCM-II)

Since class information or sample labels are crucial for classification [12], we mix them into LCPCM by imposing constraints on the penalty weighting matrix as follows:

$$w_{ij} = \begin{cases} \exp\left(-\frac{\|\mathbf{h}_i - \mathbf{h}_j\|^2}{\sigma^2}\right) & j \in N'_k(i) \\ 0 & \text{otherwise} \end{cases}, \tag{16}$$

where $N'_k(i)$ contains the indices of k nearest *intra-class* (rather than inter-class) neighbors of sample i. Through introducing the sample labels, the objective function pays more attention to the local consistency preserving of intra-class samples, and therefore the couple projection matrices are more discriminative, rather than stress on only the dimensionality reduction.

4. EXPERIMENTAL RESULTS

Our experiments are conducted on the FERET face database. The training set includes 1002 frontal face images from 429 persons. We use the standard gallery set "fa" (1196 images of 1196 individuals) and the probe set "fb" (1195 images from 1196 individuals). The 72×72 HR face images are cropped and aligned with the positions of two eyes. The 12×12 LR images are generated by smoothing and down-sampling. To evaluate the performance of our proposed method, we compare our LCPCM-I and LCPCM-II with CM and CLPM [8] methods. In our experiments, we set the distribution of each pixel to mean 0 and variance 1.

Fig. 2 illustrates the effect of parameter α on our methods. The recognition rates of both our methods vary within 3%, when α is in a suitable range. Moreover, it is obvious that the recognition rate of method LCPCM-II is approximately $2\% \sim 5\%$ higher than that of method LCPCM-I.

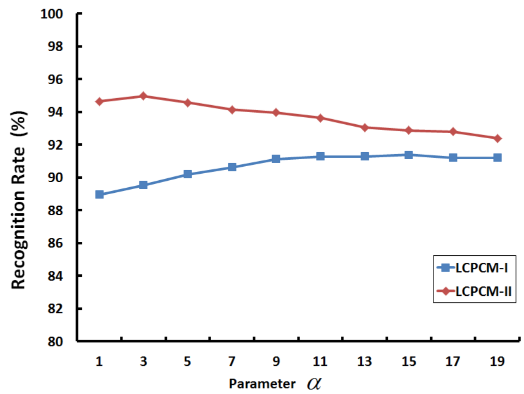

Fig. 2. Recognition results with different parameter α in heat kernel.

Fig. 3 shows the recognition results of our methods using different numbers of the nearest neighbors. It is obvious that the recognition rate of LCPCM-I drops fast as k (the number of nearest neighbors of $\mathbf{h}_i$) increases, while that of LCPCM-II barely varies. Because most classes in the train set of FERET contain only two face images, there is a high chance that LCPCM-I may involve the wrong neighbor information when $k > 1$. Nevertheless, LCPCM-II takes classification into consideration, just containing the neighbors in the same class, therefore it won't be affected.

In Fig. 4, we compare our methods with other methods (CM and CLPM), setting the parameters α a proper value and $k = 1$. The recognition rates of LCPCM-I with 85-D features and LCPCM-II with 70-D features are 91.5% and 94.9%, respectively. But CM with 144-D features and CLPM with 80-D features only achieve the rates of 77.4% and 89.5%. So our two methods are both higher than other methods. Furthermore, the recognition rates of our methods vary gently, i.e., we can obtain a relatively high recognition rate in much lower dimension for high computation speed.

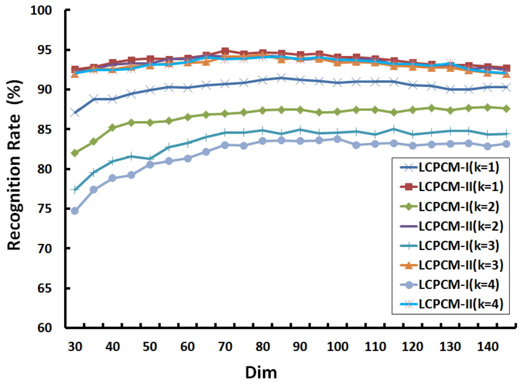

Fig. 3. Recognition results with different number of nearest neighbors.

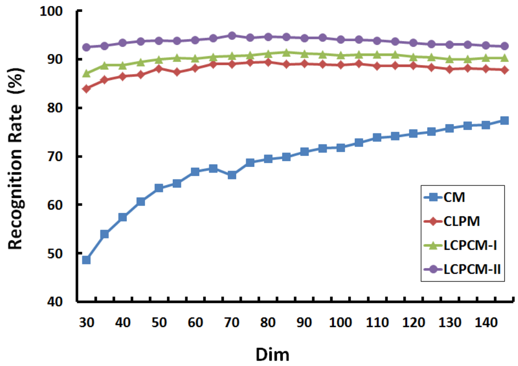

Fig. 4. Comparison of recognition results with different methods.

5. CONCLUSIONS

In this paper, we have proposed novel methods to solve low-resolution face recognition without SR preprocessing. Our algorithm projects the face images with different resolutions onto a common subspace through optimizing the objective function. The objective function preserves not only the local relationship between HR and LR space based on coupling mappings, but also that of HR and LR space themselves. We call the above algorithm LCPCM-I. Furthermore, we incorporate the classification information with LCPCM-I by drawing the sample labels into the penalty weighting matrix. We name it LCPCM-II and it achieves better perform than LCPCM-I. Experimental results on FERET show our methods can achieve pleasant performance.

In future work, employing nonlinear mapping by kernel methods and using more discriminative feature (such as Gabor wavelet, LBP, etc.) instead of the original intensity will be pursued.

6. REFERENCES

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