Multiview Face Recognition based on Canonical Correlated PCA

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Abstract: ***In video surveillance, the face recognition usually aims at recognizing a non-frontal low resolution face image from the gallery in which each person has only one high resolution frontal face image. Traditional face recognition approaches have several challenges, such as the difference of image resolution, pose variation and only one gallery image per person. This paper proposes a new method for face recognition in the case of "one sample per class" using one non-frontal LR input. FH features are super resolved from NFL input by the learnt nonlinear mappings in the coherent space. The nonlinear regression models from the specific non-frontal low resolution image to frontal high resolution features are learnt by radial basis function in subspace built by canonical correlation analysis. Extensive experiments on benchmark database show the superiority of our method.***

Keywords: Principal component analysis, Canonical correlation analysis, non-frontal face recognition, radial basis function, super resolution.

1. Introduction

Although human beings can easily detect and identify faces in a scene, it is very challenging for an automated system to achieve such objectives. Face recognition has drawn great attention in recent decades, due to its wide range commercial and law-enforcement applications [1]. The challenges become more profound when large variations exist in the face images at hand, e.g., variations in illumination conditions, viewing directions or poses, facial expression, aging, and disguises such as facial hair, glasses, cosmetics and scarves. Despite of these challenges, face recognition has drawn wide attention from researchers in areas of machine learning, computer vision, pattern recognition, neural networks, and so on. Super resolution methods are used for LR Face recognition [2], [3], [4], [5], [6]. In this paper, this work mainly focus on improving the recognition performance in the case where only a single face "snapshot" of LR is available. For feature extraction, linear PCA features of HR and LR face image sets are used [7], it gives better recognition rate and then apply the RBF-based mapping to build the regression model between the features of HR and LR face images in the coherent subspace by taking advantages of the salient features of RBF regression such as fast learning and generalization ability [14],[15],[16],[17]. RBF-based mappings [11] are built in the coherent subspaces, which favor the nearest neighbor (NN) classifier, which make the neighbors belonging to the same class as close as possible.

The rest of this paper is organized as follows. In Section 2, the system outline of Face recognition using CCA on nonlinear features is introduced. Section 3 gives brief introduction of PCA algorithm and implementation of SR method for face recognition using PCA is introduced. Section 4 gives testing phase for face recognition and followed by Result observation & Discussion in Section 5. Section 6 concludes this paper. Section 7 gives future scope of this paper.

2. System Outline

Figure 1 provides the system outline of the proposed method that super-resolves features for recognition. This approach is divided into training and testing phases. The corresponding HR and LR face image sets are used for training to obtain the base vectors of CCA transformation and the parameters of RBF regression.

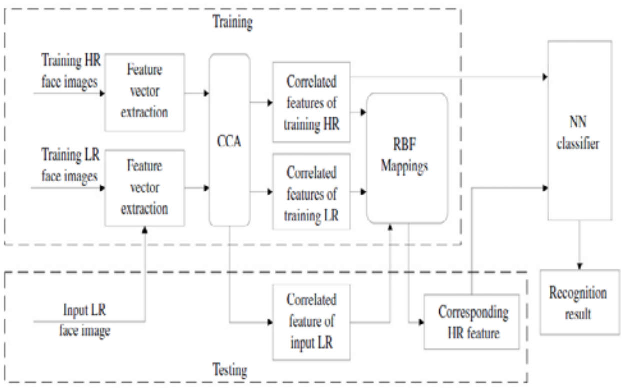


Figure 1:.Implemenataion of Super Resolution Method for Face Recognition using PCA

In the testing stage, first it calculates the PCA feature vector for a given LR image and projects the PCA features into the coherent subspace using the learnt base vectors. Hence, the SR coherent feature corresponding to the given input LR face image can be obtained by simply applying the learnt RBF mappings. And, an NN classification [16] is performed on these super-revolved features for face recognition.

The problem of SR of feature domain for face recognition is formulated as the inference of the HR domain feature $C_h$from an input LR imagel_r. Given the training sets of HR and LR face images $I^H = \{I_i^H\}_{i=1}^m = [I_1^H, I_2^H, \dots \dots \dots, I_m^H]$ and $I^L = \{I_i^L\}_{i=1}^m = [I_1^L, I_2^L, \dots \dots \dots, I_m^L]$ where m denotes the size of the training sets. The LR images with the size of 8x8 (for ORL database) and 11x14 (for UMIST database) and 46x56 (for UMIST database) images [6]. The face images of one individual for different views in ORL database are shown in figure 2 and figure 3.

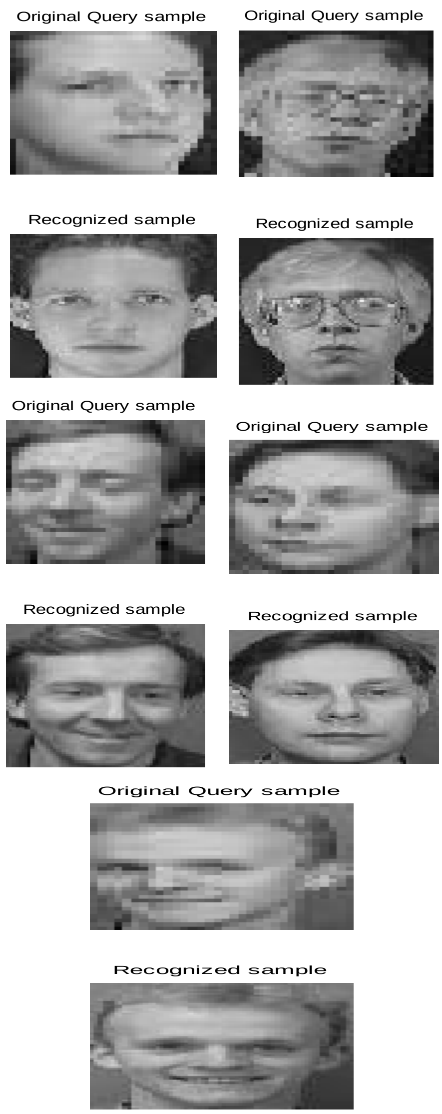
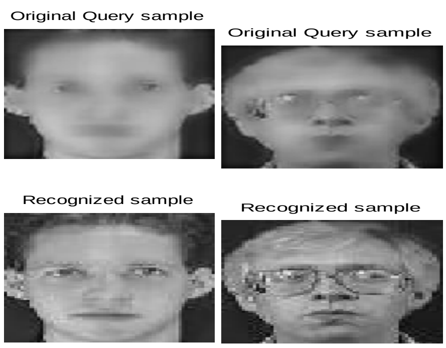


Figure 2: Face images of one individual in ORL database. (a) LR multiview query face images. (b) HR training face images



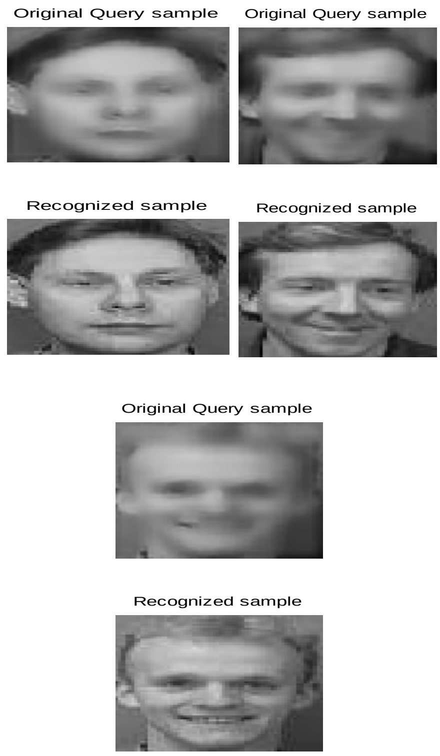


Figure 3: Face images of one individual in ORL database. (a) VLR multiview query face images. (b) HR training face images

The dimension of the image data, which is much larger than the number of training images, leads to huge computational costs.

3. Implementation of SR Method for Face Recognition Using PCA

The main idea of PCA technique is to project the samples over a subspace which maximizes the variance and minimizes the error. It is readily performed by solving an Eigenvalue problem [12], or by using iterative algorithms which estimate principal components [7]. This is done by selecting the eigenvectors corresponding to maximum eigenvalues called Principal Components of the covariance matrix. Due to huge of face images it becomes intractable to compute the eigenvectors directly. So, the holistic features of face images are obtained by classical PCA, which represents a given face image by a weighted combination of Eigen faces is given by

$$x_i^H = (B^H)^T\,(I_i^H - \mu^H)$$

Where μ^H the corresponding mean face of HR training face is images and x_i^H is the feature vector of face imageI_i^H. B^H is the feature extraction matrix obtained by the HR training face images and is made up of orthogonal Eigen vectors of $(\hat{I}^H)^T X\,(\hat{I}^H)$ corresponding to the Eigen values being ordered in descending order, where $\hat{I}^H = \{\hat{I}_i^H\}_{i=1}^{m} = [(I_1^H - \mu^H), (I_2^H - \mu^H), \ldots\ldots..(I_m^H - \mu^H)]$.

Similarly, the feature of LR face image is represented as

$$X_i^L = (B^L)^T(I_i^L - \mu^L)$$

Where B^L and μ^L are the feature extraction matrix and the mean face obtained by LR training face images, respectively.

Then, PCA feature vectors of HR and LR training sets as

$$X^H = \{X_i^H\}_{i=1}^m \in R^{pxm}$$
$$and\ X^L = \{X_i^L\}_{i=1}^m \in R^{qxm}$$

The above process of this is based on PCA feature.

Instead of linear PCA [7], [12], PCA does extract features [13] which are more useful for classification purpose. PCA has the advantages that (1) it doesn't require nonlinear optimization but the solution of an Eigen value problem and (2) by the possibility to use Gaussian kernel it comprises a fairly general class of nonlinearities that can be used.

3.1 Coherent Features

In order to learn the relationship between HR and LR feature vectors more exactly, then apply CCA [8],[9],[10]. Then, the more exact coherent SR features can be obtained for recognition in the coherent subspace. Specifically from the PCA feature training sets X^H and X^L, first subtract their mean values $\bar{X}^H$ and $\bar{X}^L$ respectively, which yields the centralized data sets $\hat{X}^H = [\hat{X}_1^H, \hat{X}_2^H, \dots \dots \dots \hat{X}_m^H]$ and $\hat{X}^L = [\hat{X}_1^L, \hat{X}_2^L, \dots \dots \dots \hat{X}_m^L]$. CCA finds two base vectors V^H and V^L for datasets $\hat{X}^H$ and $\hat{X}^L$ in order to maximize the correlation coefficient between vectors $C^H = (V^H)^T \hat{X}^H$ and $C^L = (V^L)^T \hat{X}^L$. The correlation coefficient is defined as

$$\rho = \frac{E[C^H C^L]}{\sqrt{E[(C^H)^2]E[(C^L)^2]}} = \frac{E[(V^H)^T \hat{X}^H (\hat{X}^L)^T V^L]}{\sqrt{E[(V^H)^T \hat{X}^H (\hat{X}^H)^T V^H] E[(V^L)^T \hat{X}^L (\hat{X}^L)^T V^L]}}$$

Where E [.] denotes mathematical expectation. To find the database vectors V^H and V^L, define $C_{11} = E\left[\hat{X}^H \left(\hat{X}^H\right)^T\right]$ and $C_{22} = E\left[\hat{X}^L \left(\hat{X}^L\right)^T\right]$ as the within set covariance matrices of $\hat{X}^H$ and $\hat{X}^L$ respectively, while $C_{12} = E\left[\hat{X}^H \left(\hat{X}^L\right)^T\right]$ and $C_{21} = E\left[\hat{X}^L \left(\hat{X}^H\right)^T\right]$ as their between set covariance matrices.

Then compute

$$R_1 = C_{11}^T C_{12} C_{22}^T C_{21}\ and$$
$$R_2 = C_{22}^T C_{21} C_{11}^T C_{12}$$

V^H is made up of the Eigen vectors of R_1 when the Eigen values of R_1 are ordered m descending order. Similarly, the Eigen vectors of R_2 compose V^L [9]. Then obtain the corresponding projected coefficient sets $C^H = \{C_i^H\}_{i=1}^m \in R^{pxm}$ and $C^L = \{C_i^L\}_{i=1}^m \in R^{qxm}$ of the PCA feature sets X^H and X^L projected into the coherent subspaces using the following base vectors

$$C^H = (V^H)^T \hat{X}^H$$
$$C^L = (V^L)^T \hat{X}^L$$

As there exists a coherent intrinsic structure between the HR and LR nonlinear feature sets X^H and X^L, the correlation between the two sets C^H and C^L is increased [10] and their topological structures are more coherent after the transformation. Then, the relationship between HR and LR features is more exactly established in the CCA subspace.

3.2 Nonlinear Mappings between the Coherent Features of HR and LR Face Images

As the coherent subspace is obtained, the nonlinear mapping relationship between the coherent features of HR and LR will be learned by the training features [11]. So, apply RBF to construct the mapping relationship. RBF uses radial symmetry function to transform the multivariate data approximation into the unary approximation problem. The form of RBFs used to build up function continuous approximations [12] is

$$f_i(.) = \sum_{j=1}^{m} w_i . \varphi(\left\|C^H(i) - C_j(i)\right\|)$$

Where the approximating function $f_i(.)$ is represented as a sum of m RBF's $\varphi(.)$, each associated with a different center $C_j(i)$, and w_i is the weighting coefficient. The form has been particularity used in nonlinear systems [14]. In implementation, apply multi quadric basis function

$$\varphi(.) = \sqrt{\left\|C^H(i) - C_j(i)\right\|^2 + 1}$$

In order to apply RBF's, first train the weighting coefficients by training coherent features of HR and LR faces images. The matrix from of RBF's in (18) is represented as $F = 1.\varphi$, specifically

$$[f_1, \dots . f_m] = [w_1, \dots . w_m] \begin{bmatrix} \varphi.(\|t_1 - t_1\|) & \dots \dots & \varphi.(\|t_m - t_1\|) \\ \dots . . & \dots . . & \dots . \\ \varphi.(\|t_1 - t_m\|) & \dots \dots & \varphi.(\|t_m - t_m\|) \end{bmatrix}$$

Then. The weighting coefficient matrix W is solved as

$$W = F. inv(\varphi)$$

By setting $F = C^H$ and $t_i = C_i^L$. Note that, since it is not always invertible, we need to perform a regularization operation, i.e., $\varphi + \tau I$. Where τ is set to a small positive value such as $\tau = 10^{-3}$, and I is the identify matrix. Based in the trained RBFs, the SR coherent features of a given LR coherent features can be obtained [7].

4. Testing Phase

Given an LR face image I_l, the PCA [13] feature vector x_l of the input face image is computed by using the N-by-N Gaussian kernel. Use the kernel-trick K_cntr^L (taken from training phase section 3.1).

$$x_l = \left(K_{cntr}{}^L\right)^T (I_l - \mu^L)$$

In this approach, recognition process is done in the coherent subspace [9]. So, the PCA facture vector x_l is transformed to the coherent subspace as

$$C_l = (V^L)^T (F_q - \bar{x}^L)$$

The coherent HR feature vector (C_{hq}) corresponding LR feature is obtained by feeding the coherent feature of the LR face C_l to the trained RBF mapping [11] in (18).

$$C_{hq} = W.[\varphi.(C_1^L, C_l) \ldots \ldots .. \varphi.(C_m^L, C_l)]^T$$

Finally, apply the coherent feature C_{hq} and $C^H = \{C_i^H\}_{i=1}^m$ for recognition based on the NN classification [16] with L_2 norm $g_k(C_{hq}) = \min\left(\left\|C_{hq} - c_{ik}^H\right\|\right) \quad i = 1,2, \ldots . m$

Where c_{ik}^H represents i^{th} sample in the k^{th} class in C^H.

5. Result Observation

To analyze the performance of the super resolution method using nonlinear feature extraction PCA, Two sets of experiments are performed on face image databases: ORL [17]. The databases are chosen so as to cover a wide range of possible variations of face images due to expression illumination and pose. The ORL database is used to evaluate the performance of the system under conditions where slight pose, imprecise face alignments and expressions vary. The average recognition rates are tabulated when all the discriminant vectors are considered.

To start the FR experiments, each one of the two databases is randomly partitioned into a training sets and a test sets with no overlap between the two. The partitions of the databases are done as follows: ORL includes 40 individuals, and each has 10 different face images. For each individual in ORL database, randomly chosen different sizes of Training sets (2 samples per class, 3 samples per class, 5 samples per class, 7 samples per class, 8 samples per class) and corresponding testing sets (8 samples per class, 7 samples per class, 5 samples per class, 3 samples per class, 2 samples per class) are formed. In order to evaluate the recognition rate accurately, recognition rates are averaged over 2 runs and are tabulated in Table 1 for ORL using all the discriminant features. Table 2 shows the recognition rates with varying feature dimensions with 5 samples per ORL database. From these results the recognition rate increases with an increase in number of training images. Comparing the PCA feature extraction the nonlinear approach PCA achieves higher recognition rates under the variations of expression, pose and a wide range of multi view face images.

Table 1: The average percentage of face recognition rates over two runs for ORL data base

No. of Training samples	*Previous*	*Proposed*
2	88.28	92.28
3	89.29	93.93
5	94.50	95.50
7	95.62	96.87

Table 2: the percentage of recognition result with different feature dimensions of ORL database

Size	*PCA*	*CLPM[7]*
20	90.25	84
30	91.50	87
40	91.50	89
50	92.50	89

6. Conclusion

The face recognition system is degrading its performance by LR images. To address this problem, an SR method in the feature domain for face recognition was proposed in this paper. By the use of integral kernel functions, it can efficiently compute principal components in high-dimensional feature spaces. CCA transformation to the PCA feature sets of HR and LR face images in order to find the coherent feature subspaces. A non-linear mapping between HR/LR features can be built by RBFs with lower regression errors in the coherent feature space than in the PCA feature space [13]. Hence, the SR coherent feature corresponding to an input LR face image was obtained by simply applying the learnt RBF mappings. And, face identity can be obtained by feeding these SR features to a simple NN classifier. Compared to other feature domain SR methods, the proposed method is more robust under the variations of expression, pose and down-sampling rate and has a higher recognition rate. CCA was applied to the PCA features to form the coherent features for recognition, but it is applicable to other holistic face recognition features such as independent component analysis [2] and discrete cosine transform features [19], which might improve the recognition performance further.

7. Future Scope

In future the efficiency of face recognition can be increased by performing the genomic comparison which increases the recognition rate and also reduces the time complexity. Under this comparison the internal features of the face image are going to be extracted and trained into database. At the time of testing the comparison also takes place with these genomic features only. Its main attraction being is its simple underlying concepts and ease of implementation.

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