Synthesis-based Recognition of Low Resolution Faces

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Abstract

Recognition of low resolution face images is a challenging problem in many practical face recognition systems. Methods have been proposed in the face recognition literature for the problem when the probe is of low resolution, and a high resolution gallery is available for recognition. These attempts modify the probe image such that the resultant image provides better discrimination. We, however, formulate the problem differently by leveraging the information available in the high resolution gallery image and proposing a generative approach for classifying the probe image. An important feature of our algorithm is that it can handle resolution changes along with illumination variations. The effectiveness of the proposed method is demonstrated using standard datasets and a challenging outdoor face dataset. It is shown that our method is efficient and can perform significantly better than many competitive low resolution face recognition algorithms.

1. Introduction

Face recognition (FR) has been an active field of research in biometrics for over two decades [23]. Current methods work well when the test images are captured under controlled conditions. However, quite often the performance of most algorithms degrades significantly when they are applied to face images taken under uncontrolled conditions where there is no control over pose, illumination, expressions and resolution of the face image. Image resolution is an important parameter in many practical scenarios such as surveillance where high resolution cameras are not deployed due to cost and data storage constraints and further, there is no control over the distance of human from the camera. Figure 1 illustrates a practical scenario where one is faced with a challenging problem of recognizing humans when the captured face images are of very low resolution (LR).

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Figure 1. A typical image in remote face recognition.

Many methods have been proposed in the vision literature that can deal with this resolution problem in FR. Most of these methods are based on some application of super-resolution (SR) technique to increase the resolution of images so that the recovered higher-resolution (HR) images can be used for recognition. One of the major drawbacks of applying SR techniques is that there is a possibility that recovered HR images may contain some serious artifacts. This is often the case when the resolution of the image is very low. As a result, these recovered images may not look like the images of the same person and the recognition performance may degrade significantly.

In practical scenarios, the resolution change is also coupled with other variations due to pose, illumination variations and expression. Algorithms specifically designed to deal with LR images quite often fail in dealing with these variations. Hence, it is essential to include these parameters while designing a robust method for low-resolution FR. To this end, in this paper, we present a generative approach to low-resolution FR that is also robust to illumination variations based on learning class specific dictionaries. One of the major advantages of using generative approaches is that they are known to have reduced sensitivity to noise than the discriminative approaches [23].

The training stage of our method consists of three main steps. In the first step of the training stage, given HR training samples from each class, we use an image relighting method to generate multiple images of the same subject with different lighting so that robustness to illumination changes can be realized. In the second step, the resolution of the enlarged gallery images from each class is matched with that of the probe image. Finally, in the third step, class and resolution specific dictionaries are trained for each class. For the testing phase, a novel LR image is projected onto the span of the atoms in each learned dictionary. The residual vectors are then used to classify the subject. A flowchart of the proposed algorithm is shown in figure 2.

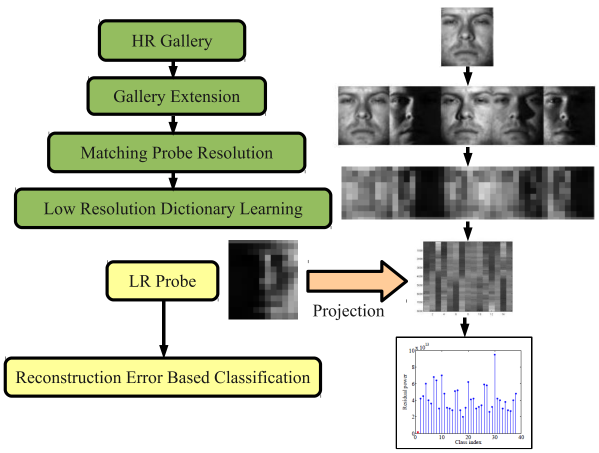

Figure 2. Overview of our algorithm.

1.1. Paper organization

The rest of the paper is organized as follows: In Section 2, we review a few related works. In Section 3, the proposed approach is described. We demonstrate experimental results in Section 4 and computational efficiency of the algorithm in Section 5. Finally, Section 6 concludes the paper with a brief summary and discussion.

2. Previous Work

In this section, we review some of the recent FR methods that can deal with poor resolution. These techniques can be broadly divided into the following categories.

SR-based approaches: SR is the method of estimating a HR image $\mathbf{x}$ given a downgraded image $\mathbf{y}$. The LR image model is often given as

$$\mathbf{y} = \mathbf{B}\mathbf{H}\mathbf{x} + \eta \tag{1}$$

where $\mathbf{B}, \mathbf{H}$ and η are the down-sampling matrix, the blurring matrix and the noise, respectively. Earlier works for solving the above problem were based on taking multiple LR inputs and combining them to produce the HR image. A classical work by Baker and Kanade [4] showed that methods based on multiple LR images and smooth priors would fail to produce good results as the resolution factor increases. They also proposed a face hallucination method for super-resolving face images. Subsequently, there have been works using a single image for SR such as example-based SR [9], SR using neighborhood embedding [8] and sparse representation-based SR [22]. SR based methods have also been proposed for specifically handling the problem of low-resolution FR. In particular, an eigen-face domain SR method for FR was proposed by Gunturk *et al.* in [11]. This method proposes to solve the FR at LR using SR of multiple LR images using their PCA domain representation. Given a LR face image, Jia and Gong [13] propose to directly compute a maximum likelihood identity parameter vector in the HR tensor space that can be used for SR and recognition. Hennings-Yeomans *et al.* [12] presented a Tikhonov regularization method that can combine the different steps of SR and recognition in one step.

Metric learning-based approaches: Though the LR faces are directly not suitable for face recognition purpose, it is also not necessary to super-resolve the image before recognition, as the problem of recognition is not the same as SR. Based on this motivation, some different approaches to this problem have been suggested. The Coupled Metric Learning method [16] attempts to solve this problem by mapping the LR image to a new subspace, where higher recognition can be achieved. Extension of this method was recently proposed in [17]. A similar approach for improving the matching performance of the LR images using multidimensional scaling was recently proposed by Biswas *et al.* in [6].

Other methods: Additional methods for LR FR include correlation filter-based approach [1] and a support vector data description method [15]. 3D face modeling has also been used to address the LR face recognition problem in [18] [20]. There have been efforts to solve the problem of unconstrained low resolution FR using videos. In particular, Arandjelovic and Cipolla [3] use a video database of LR face images with pose and illumination variations.

3. Proposed Approach

In this section, we present the details of our proposed low-resolution FR algorithm based on learning class specific dictionaries.

3.1. Image Relighting

As discussed earlier, the resolution change is usually coupled with other parameters such as illumination variation. In this section, we introduce an image relighting method that can deal with this illumination problem in LR face recognition. Rather than modifying the LR image, the idea is to capture various illumination conditions in the training samples.

We assume the Lambertian reflectance model for the facial surface. The surface normals, albedo and the intensity image are related by an image formation model. For Lambertian objects, the diffused component of the surface reflection is modeled using the Lambert's Cosine Law given by

$$I = \rho \max(\mathbf{n}^T \mathbf{s}, 0), \tag{2}$$

where I is the pixel intensity, $\mathbf{s}$ is the light source direction, ρ is the surface albedo and $\mathbf{n}$ is the surface normal of the corresponding surface point. Using this model, a non stationary stochastic filtering framework was recently proposed in [5] to estimate the albedo from a single image. We adapt this method to first estimate the albedo map from a given face image. Then, using the estimated albedo map, we generate new images under any illumination condition using the image formation model (2). This can be done by combining the estimated albedo map with the average facial information [7].

It was shown in [14] that an image of an arbitrarily illuminated object can be approximated by a linear combination of the image of the same object in the same pose, illuminated by nine different light sources placed at preselected positions. Hence, the image formation equation can be rewritten as

$$I = \sum_{i=1}^{9} a_i I_i, \tag{3}$$

where $I_i = \rho \max(\mathbf{n}^T \mathbf{s}_i, 0)$, and $\{\mathbf{s}_1, \cdots, \mathbf{s}_9\}$ are the prespecified illumination directions. Since, the objective is to generate HR gallery images which will be sufficient to account for any illumination in the probe image, we generate images under pre-specified illumination conditions and use them in the gallery. Figure 3 shows some relighted HR images along with the corresponding input and LR images. Furthermore, as the condition is true irrespective of the resolution of LR image, the same set of gallery images can be used for all resolutions.

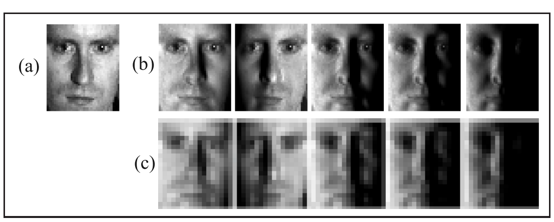

Figure 3. Examples of (a) original image and the corresponding (b) relighted and (c) LR images with different lighting from the PIE dataset.

3.2. Low Resolution Dictionary Learning

Suppose that we are given C distinct face classes and a set of m_i HR training images per class, $i = \{1, \cdots, C\}$. Here, m_i corresponds to the total number of images in class i including the relighted images. We identify an $r_H \times q_H$ gray-scale image as an N_H-dimensional vector, $\mathbf{x}$, which can be obtained by stacking its columns, where $N_H = r_H \times q_H$. Let

$$\tilde{\mathbf{X}}_i = [\mathbf{x}_{i1}, \cdots, \mathbf{x}_{im_i}] \in \mathbb{R}^{N_H \times m_i}$$

be an $N_H \times m_i$ matrix of training images corresponding to the i^{th} class. For resolution robust recognition, the matrix $\widetilde{\mathbf{X}}_i$ is pre-multiplied by a down-sampling $\mathbf{B}$ and blurring $\mathbf{H}$ matrices. Here, $\mathbf{H}$ has a fixed dimension of $N_H \times N_H$ and $\mathbf{B}$ will be of size $N_L \times N_H$, where $N_L = r_L \times q_L$, the LR probe being a gray-scale image of $r_L \times q_L$. The resolution specific training matrix, $\mathbf{X}_i$ is thus created as

$$\mathbf{X}_i = \mathbf{B}\mathbf{H}\widetilde{\mathbf{X}}_i = (\widetilde{\mathbf{X}}_i) \downarrow \tag{4}$$

As the columns of $\mathbf{X}_i$ define a subspace (Equation 3), we seek to learn a class-specific dictionary $\mathbf{D}_i \in \mathbb{R}^{N_L \times K}$, K being the number of prototype atoms, such that columns of $\mathbf{X}_i$ are best represented by linear combination of its atoms. We further impose a sparsity constraint on the number of atoms of dictionary used in the representation to constraint the solution space of representation problem. One can obtain this by finding $\mathbf{D}_i$ and a sparse matrix Γ_i that minimizes the following representation error

$$(\hat{\mathbf{D}}_\mathbf{i}, \hat{\Gamma}_i) = \arg \min_{\mathbf{D}_i, \Gamma_i} \|\mathbf{X}_i - \mathbf{D}_i \Gamma_i\|_F^2 \text{ s. t. } \forall k \ \|\gamma_k\|_0 \leq T_0 \tag{5}$$

where γ_k represent the columns of Γ_i and the ℓ_0 sparsity measure $\|.\|_0$ counts the number of nonzero elements in the representation. T_0 is the desired sparsity level. Here, $\|\mathbf{A}\|_F$ denotes the Frobenius norm defined as $\|\mathbf{A}\|_F = \sqrt{\sum_{ij} \mathbf{A}_{ij}^2}$. We implemented above optimization problem using the well-known K-SVD algorithm [2].

3.3. Classification

Given an $r_L \times q_L$ LR probe, it is column-stacked to give the column vector $\mathbf{y}$. It is projected onto the span of the atoms in each $\mathbf{D}_i$ of the C class dictionary, using the orthogonal projector $\mathbf{P}_i = \mathbf{D}_i(\mathbf{D}_i^T \mathbf{D}_i)^{-1} \mathbf{D}_i^T$. The approximation and residual vectors can then be calculated as

$$\hat{\mathbf{y}}^i = \mathbf{P}_i \mathbf{y} = \mathbf{D}_i \alpha^i \tag{6}$$

and

$$\mathbf{r}^i(\mathbf{y}) = \mathbf{y} - \hat{\mathbf{y}}^i = (\mathbf{I} - \mathbf{P}_i)\mathbf{y}, \tag{7}$$

respectively, where $\mathbf{I}$ is the identity matrix and

$$\alpha^i = (\mathbf{D}_i^T \mathbf{D}_i)^{-1} \mathbf{D}_i^T \mathbf{y} \tag{8}$$

are the coefficients. As the dictionary, $\mathbf{D}_i$, has the best representation for each example in $\mathbf{X}_i$, $\|\mathbf{r}^i(\mathbf{y})\|_2$ will be small if $\mathbf{y}$ were to belong to the i^{th} class and large for the other classes. Based on this, we can classify $\mathbf{y}$ by assigning it to the class, $d \in \{1, \cdots, C\}$, that gives the lowest reconstruction error, $\|\mathbf{r}^i(\mathbf{y})\|_2$:

$$d = \text{identity}(\mathbf{y}) \\ = \arg\min_i \|\mathbf{r}^i(\mathbf{y})\|_2. \quad (9)$$

3.4. Generic Dictionary Learning

The class-specific dictionary, $\mathbf{D}_i, i = 1, \cdots, C$ learned above can be extended to use features other than intensity images. Specifically, the dictionary can be learned using features like Eigenbasis, $\widetilde{\mathbf{F}}_i$ extracted from training matrix $\widetilde{\mathbf{X}}_i$. However, as equation (4) does not hold for $\widetilde{\mathbf{F}}_i$, the resolution specific feature matrix $\mathbf{F}_i$ is directly extracted using $\mathbf{X}_i$. Our Synthesis-based LR FR (SLRFR) algorithm is summarized in figure 4.

Given a LR test sample $\mathbf{y}$ and C training matrices $\widetilde{\mathbf{X}}_1, \cdots, \widetilde{\mathbf{X}}_C$ corresponding to HR gallery images.

Procedure:

- For each training image, use the relighting approach described in section 3.1 to generate multiple images with different illumination conditions and use them in the gallery.
- Learn the best dictionaries $\mathbf{D}_i$, to represent the resolution specific enlarged training matrices, $\mathbf{X}_i$, using the K-SVD algorithm, where $\mathbf{X}_i = (\widetilde{\mathbf{X}}_i) \downarrow$, $i = 1, \cdots, C$.
- Compute the approximation vectors, $\hat{\mathbf{y}}^i$, and the residual vectors, $\mathbf{r}^i(\mathbf{y})$, using (6) and (7), respectively for $i = 1, \cdots, C$.
- Identify $\mathbf{y}$ using (9).

Figure 4. The SLRFR algorithm.

4. Experiments

To demonstrate the effectiveness of our method, we present experimental results on various face recognition datasets. For all the experiments, we learned the dictionary elements using the PCA features.

4.1. CMU-PIE dataset

The PIE dataset [21] consists of 68 subjects under different illumination conditions. Each subject has 21 face images under different illumination conditions.

Implementation To test our method and compare with the existing methods [17] [6], we chose first 34 subjects with 6 randomly chosen illuminations as the training set. For the remaining 34 subjects and the 15 illumination conditions, the experiment was done by choosing one gallery image per subject and taking the remaining as the probe image. The procedure was repeated for all the images and the final recognition rate was obtained by averaging over all the images. The size of the HR images was fixed to 48×40. The LR images were obtained by smoothing followed by downsampling the HR images. The experiments were done at resolutions of 12×10, 10×8 and 7×6, thus validating the method across resolutions. We also tested the CLPM algorithm [17] and PCA performances on the expanded gallery to get a fair comparison. Results from other algorithms as reported in the original papers were also tabulated.

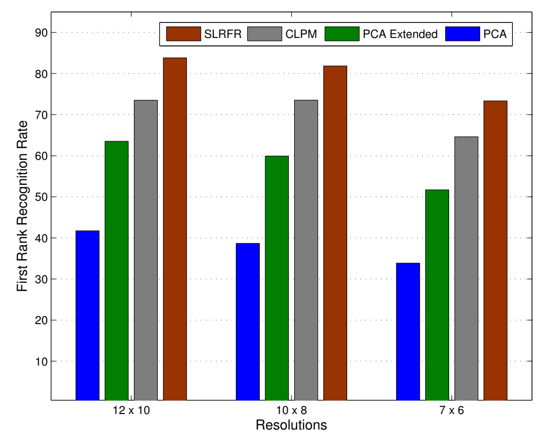

Figure 5. Recognition Rates for PIE data with probes at low resolutions

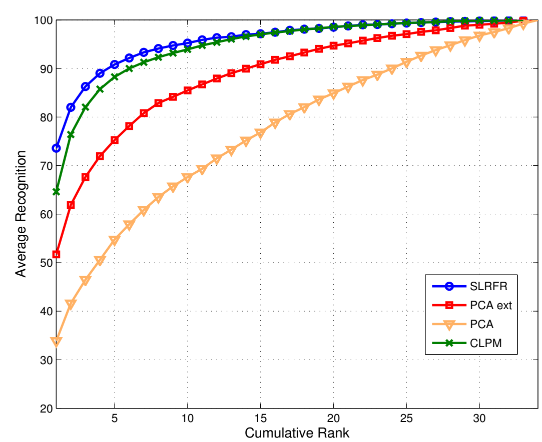

Figure 6. CMC Curves for PIE data with probes at 7×6 resolution

Resolution	MDS [6]	SLRFR
7×6	55.0%	**76.0%**
12×10	73.0%	**83.8%**
19×16	78.0%	**87.1%**

Table 1. Comparisons for rank one recognition of PIE dataset rate

Observations Figure 5, 6 and Table 1 show that the proposed method clearly outperforms previous algorithms. The proposed algorithms shows over 30% improvement over PCA performance with the original gallery set at rank one recognition rate and 8% better than the CLPM method at the lowest probe resolution. PCA using the extended gallery set also improves the performance over using a single gallery image. This shows that our method of gallery extension can be coupled with the existing face recognition algorithms to improve performance at low resolutions.

4.2. FRGC Dataset

We also evaluated on Experiment 1 of the FRGC dataset [19]. It consists of 152 gallery images, each subject having one gallery and 608 probe images under controlled setting. A separate training set of 183 images is also available which was used to learn the PCA basis.

Implementation The resolution of the HR image was fixed at 48×40 and probe images at resolutions of 12×10, 10×8 and 7×6 were created by smoothing and down-sampling the HR probe images.

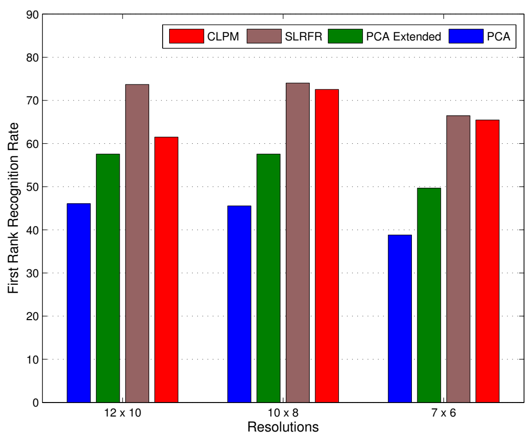

Figure 7. Recognition Rates for FRGC data with probes at low resolutions

Resolution	MDS [6]	S2R2 [12]	VLR [24]	SLRFR
6×6	-	55.0%	-	**62.9%**
7×6	-	-	55.5%	**63.8%**
9×7	58.0%	-	-	**72.2%**

Table 2. Comparisons for rank one recognition rate of FRGC dataset

Observations The results from Figure 7 and Table 2 demonstrate that the proposed method gives better performance over the existing methods. The CLPM algorithm performs close to the proposed method at 7×6 and 10×8 resolutions, but its performance decreases at 12×10. This shows that the method is not stable over different resolutions. The proposed method, however, gives a consistent performance over all the resolutions.

4.3. Outdoor Face Dataset

We also tested our method on a challenging outdoor face dataset. The database consists of face images of 18 individuals at different distances from camera. We chose a subset of 90 low resolution images, which were also corrupted with blur, illumination and pose variations. 5 high resolution, frontal and well-illuminated images were taken as the gallery set for each subject. The images were aligned using 5 manually selected facial points. The gallery resolution was fixed at 120×120 and the probe resolution at 20×20. Figure 8 shows some of the gallery images and the low quality probe images. As the LR probes were suffering from illumination as well as blur and pose problems, the assumption in Equation 3 is not completely valid. Hence, class-wise dictionaries were learned just using Eigenbasis of original down-sampled gallery images. Furthermore, instead of class-wise reconstruction error based classification, we used robust ℓ-1 projection and SVM-based classifier for recognition. The recognition rates for the dataset are shown in Table 3. We compare our method with that of the Regularized Discriminate Analysis (RDA) [10] and [17]. For the reg LDA comparison, we first used the PCA as a dimensionality reduction method to project the raw data onto an intermediate space, then we used the RDA to project the PCA coefficients onto a final feature space. These two procedures guarantee that the within-class scatter matrix is non-singular. Then, the final low-dimensional discriminate features are fed into an SVM for classification.

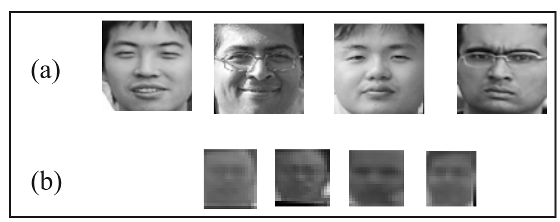

Figure 8. Example images from the outdoor face dataset (a) HR gallery images (b) LR probe images

Method	Recognition Rate
reg LDA+SVM	60%
SLRFR	**67.8%**
CLPM [17]	16.7%

Table 3. Performance for the Outdoor Face Dataset

Observations It can be seen from the table that SLRFR outperforms the other algorithms on this difficult outdoor face dataset. The CLPM algorithm performs rather poorly on this dataset because the dataset contains variations other than LR and CLPM is not able to deal with these variations. During the learning phase, by keeping the sparsity low enough, our method is able to keep the internal structure of each subject while being robust to noise and distortion present in the dataset.

5. Computational Efficiency

All the experiments were conducted using 2.13GHz Intel Xeon processor on Matlab programming interface. The gallery extension step using relighting took an average of $2s$ per gallery image of size 48×40. The K-SVD Dictionary took on an average $0.07s$ to train each class, while classification of a probe image was done in an average of $0.1s$ at the resolution of 7×6. Thus, the proposed algorithm is computationally efficient . Further, as the extended gallery can be used for all resolutions, it can be computed once and stored for a database.

6. Discussion and Conclusion

We have proposed an algorithm which can provide good accuracy for low resolution images, even when a single HR gallery image is provided per person. While the method avoids the complexity of previously proposed algorithms, it is also shown to provide state-of-the-art results when the LR probe differ in illumination from the given gallery image. The idea of exploiting information in HR gallery image is novel and can be used to expand the limits of remote face recognition. Future extensions to this work will be to extend the proposed method to account for other variations such as pose, expression, etc. The present classification using reconstruction error can be studied further to explore a mix of discriminative and re-constructive techniques to further improve the recognition.

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