

Multidimensional Scaling for Matching Low-resolution Facial Images

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Abstract—Face recognition performance degrades considerably when the input images are of poor resolution as is often the case for images taken by surveillance cameras or from a large distance. In this paper, we propose a novel approach for the recognition of low resolution images using multidimensional scaling. From a resolution point of view, the scenario yielding the best performance is when both the probe and gallery images are of high enough resolution to discriminate across different subjects. The proposed method embeds the low resolution images in an Euclidean space such that the distances between them in the transformed space approximates the *best distances* had both the images been of high resolution. The mapping is learned from high resolution training images and their corresponding low resolution images using iterative majorization algorithm. Extensive evaluation of the proposed approach on different datasets like PIE and FRGC with resolution as low as 7×6 pixels illustrates the usefulness of the method. We show that the proposed approach significantly improves the matching performance as compared to performing standard matching in the low-resolution domain. Performance comparison with different super-resolution techniques which obtains higher-resolution images prior to recognition further signifies the effectiveness of our approach.

I. INTRODUCTION

Face recognition with its wide range of commercial and law enforcement applications has been one of the most important areas of research in the field of computer vision and pattern recognition. Though current algorithms perform well on images captured in controlled environments, their performance is far from satisfactory for images taken under uncontrolled scenarios [1]. Recently, the proliferation of surveillance cameras for security and law-enforcement applications has necessitated the development of algorithms which are more suited for handling the kind of images captured by these cameras. Due to the large distance of the camera from the subject, these images usually have very poor resolution which considerably degrades the performance of traditional face recognition algorithms developed for good quality images. Discriminatory properties present in the facial images used for distinguishing one person from the other is often lost due to decrease in resolution resulting in unsatisfactory performance. In addition to being able to handle low-resolution (LR) images, the algorithms must be efficient enough to handle the large amount of data captured continuously by the surveillance cameras. Though a lot of work has been done on the problem of face recognition to

address issues like illumination and pose variations, it is only recently that efforts have been made to deal with LR face images.

Much of the existing research which addresses the problem of matching LR images relies on super-resolution techniques to obtain higher resolution images [2][3] which are then used for recognition. Most of these approaches aim to obtain a good high resolution reconstruction and are not optimized from the recognition perspective. Recently, Yeomans *et al.* [4] proposed to perform super-resolution and recognition simultaneously and obtained impressive recognition results for matching LR probe images with HR gallery images. But in their approach, given a probe image, the optimization needs to be repeated for each gallery image in the database resulting in high computational overhead, specially for databases of large-size.

In this work, we propose a novel approach for improving the matching performance of LR images using Multidimensional Scaling (MDS). Clearly, the scenario yielding the best performance occurs when both the gallery and probe images are of high resolution. The proposed method embeds the LR gallery and probe images in an Euclidean space such that the distances between them in the transformed space approximates the *best distances*, had both the images been of high resolution. We show how the mapping for transforming the LR images can be learnt using MDS. Iterative majorization technique is used to learn the transformation from HR training images and their corresponding LR images. The transformation can be learned off-line from the training images thus making the approach very efficient. During testing, the input images are transformed using the learned transformation matrix and then matching is performed.

Extensive experiments are performed to evaluate the effectiveness of the proposed approach on the PIE and FRGC dataset. In all cases, the proposed approach significantly improves the matching performance as compared to performing standard matching in the low-resolution domain. We also provide performance comparison with different super-resolution techniques which obtains higher-resolution images prior to recognition to further signify the effectiveness of our approach.

A. Organization of the paper

The rest of the paper is organized as follows. Section II discusses a few related works. The problem definition is given in Section III. The details of the proposed approach for

*This work is supported by the Biometrics Task Force and the Technical Support Working Group through US Army contract W91CRB-08-C-0093.

matching LR images is discussed in Section IV. The results of experimental evaluation are presented in Section V. The paper concludes with a summary and discussion.

II. PREVIOUS WORK

In this section, we discuss the existing approaches in the literature which address the problem of face recognition from images of poor resolution. Most of the current approaches follow a super-resolution approach [2][3][5] and many of these approaches use face priors to obtain better image reconstruction. Chakrabarti *et al.* [3] proposed a learning-based method using kernel principal component analysis for deriving prior knowledge about the face class for performing super-resolution. Freeman *et al.* [6] explored training-based super-resolution algorithms in which the fine details corresponding to different image regions seen at a low-resolution is learned from a training set and then these learned relationships are used to predict fine details in other images. Liu *et al.* [5] proposed a two-step statistical modeling approach for hallucinating a HR face image from a LR input. The relationship between the HR images and their corresponding down-sampled and smoothed LR images is learned using a global linear model and the residual high-frequency content is modeled by a patch-based non-parametric Markov network. Many other super-resolution based approaches have also been proposed [7][8][9]. Yang *et al.* [17][18] addresses the problem of generating a super-resolution image from a low-resolution input image from the perspective of compressed sensing.

The main aim of these techniques is to produce a high resolution image from the low-resolution input using assumptions about the image content, and they are not designed (or optimized) from a matching perspective. Since many face recognition systems use an initial dimensionality reduction method, Gunturk *et al.* [11] proposed eigenface-domain super-resolution in the lower dimensional face space. Several super-resolution approaches also try to reconstruct a high resolution image from a sequence of input images [10]. Some other approaches like support vector data description [12] and advanced correlation filters [13] have also been used to address this problem.

Recently, Hennings-Yeomans *et al.* [4] proposed an approach to perform super-resolution and recognition simultaneously. Using features from the face and super-resolution priors, the authors aim to extract a high resolution template that simultaneously fits the super-resolution as well as the face-feature constraints. Arandjelovic and Cipolla [14] propose a generative model for separating the illumination and down-sampling effects. The person-specific down-sampling effects are learnt using enrolled person's training sequences for the problem of matching a LR probe video with a HR gallery video. Given a LR face image, Jia and Gong [15] propose directly computing a maximum likelihood identity parameter vector in the HR tensor space which can be used for recognition and reconstruction of HR face images.

III. PROBLEM DEFINITION

In this section, we describe the proposed formulation for improving the recognition of LR images using MDS approach. We assume that the training set consists of good HR images and LR images of the same subjects. The HR and LR images of the same subject need not be obtained under the same imaging conditions. Let the HR training images be denoted by \mathbf{I}_i^h , $i = 1, 2, \dots, N$ and the corresponding LR images be denoted by \mathbf{I}_i^l , where N is the number of images. (In the absence of HR and LR images of the same subject, the LR images can be generated from the HR images by downsampling and smoothing.) Let \mathbf{x}_i^h and \mathbf{x}_i^l denote the features of the high and low resolution images respectively and $d_{i,j}^h$ denote the distance between the feature vectors \mathbf{x}_i^h and \mathbf{x}_j^h corresponding to the HR images. Clearly, the best scenario is when the input images have high resolution. Decrease in resolution results in loss of discriminatory properties required to distinguish between different subjects, thus affecting the recognition performance. Here we want to transform the input LR images in such a way that the distances between them emulates the *best possible* distances given by $d_{i,j}^h$, which would have been the case had the images been of high resolution.

IV. PROPOSED APPROACH

Here we derive the mapping required to transform the features from the LR images such that the distance between them approximates $d_{i,j}^h$ in the transformed space. Let $\mathbf{f} : R^d \rightarrow R^m$ denote the mapping from the R^d input feature space (corresponding to the LR inputs) to the embedded Euclidean space R^m . Here m is the dimension of the transformed space and d denotes the input dimension. We consider the mapping $\mathbf{f} = (f_1, f_2, \dots, f_m)^T$ to be a linear combination of p basis functions of the form

$$f_i(\mathbf{x}^l; \mathbf{W}) = \sum_{j=1}^p w_{ji} \phi_j(\mathbf{x}^l) \quad (1)$$

where $\phi_j(\mathbf{x}^l); j = 1, 2, \dots, p$ can be a linear or non-linear function of the input feature vectors. Here $[\mathbf{W}]_{ij} = w_{ij}$ is the $p \times m$ matrix of the weights to be determined. The mapping defined by (1) can be written in a compact manner as follows

$$\mathbf{f}(\mathbf{x}^l; \mathbf{W}) = \mathbf{W}^T \phi(\mathbf{x}^l) \quad (2)$$

The goal is to transform the feature vectors of the LR images such that the distance between the transformed feature vectors approximates the best possible distance $d_{i,j}^h$. So we want to find the matrix \mathbf{W} which minimizes the following objective function

$$\mathbf{J}_{\text{DP}}(\mathbf{W}) = \sum_{i=1}^N \sum_{j=1}^N (q_{ij}(\mathbf{W}) - d_{i,j}^h)^2 \quad (3)$$

Here N is the number of HR (and LR) training images, $q_{ij}(\mathbf{W}) = |\mathbf{W}^T (\phi(\mathbf{x}_i^l) - \phi(\mathbf{x}_j^l))|$ is the distance between the transformed feature vectors of the i^{th} and j^{th} LR training images. The distance between the corresponding HR images

is $d_{i,j}^h$. Note that the distance $q_{i,j}(\mathbf{W})$ and thus the objective function depends on the transformation matrix \mathbf{W} .

Since our goal here is improved matching of LR images, the objective function in (3) can be modified to include class information available during training. Thus, the resulting objective function consists of a distance preservation term (same as \mathbf{J}_{DP}) and a class separability term (\mathbf{J}_{CS}) as follows

$$\begin{aligned} \mathbf{J}(\mathbf{W}) &= \lambda \mathbf{J}_{DP} + (1 - \lambda) \mathbf{J}_{CS} \\ &= \lambda \sum_{i=1}^N \sum_{j=1}^N (q_{i,j}(\mathbf{W}) - d_{i,j}^h)^2 + \\ &\dots (1 - \lambda) \sum_{i=1}^N \sum_{j=1}^N \delta(\omega_i, \omega_j) q_{i,j}^2(\mathbf{W}) \end{aligned} \quad (4)$$

The first term \mathbf{J}_{DP} is the distance preserving term which ensures that the distance between the transformed feature vectors approximates the distance $d_{i,j}^h$. \mathbf{J}_{CS} is a class separability term to further facilitate discriminability. ω_i denotes the class label of the i^{th} class. The parameter λ controls the relative effect of the distance preserving and the class separability on the total optimization. A simple form of the class separability term is given by [19]

$$\begin{aligned} \delta(\omega_i, \omega_j) &= 0; & \omega_i \neq \omega_j \\ &= 1; & \omega_i = \omega_j \end{aligned} \quad (5)$$

This specific form of the class separability term penalizes larger distances between data points of the same class. More complicated terms may also be seamlessly used with the formulation.

The goal is to compute the transformation matrix \mathbf{W} by minimizing the objective function given by (4). Separating the terms containing the transformation matrix, the objective function can be rewritten as

$$\begin{aligned} \mathbf{J}(\mathbf{W}) &= \sum_{i=1}^N \sum_{j=1}^N \alpha_{i,j} (q_{i,j}(\mathbf{W}) - \beta_{i,j} d_{i,j}^h)^2 + \\ &\dots \lambda \sum_{i=1}^N \sum_{j=1}^N \gamma_{i,j} (d_{i,j}^h)^2 \end{aligned} \quad (6)$$

The expression for the different terms are given by

$$\begin{aligned} \alpha_{i,j} &= (1 - \lambda) \delta(\omega_i, \omega_j) + \lambda \\ \beta_{i,j} &= \frac{\lambda}{\alpha_{i,j}} \quad \text{and} \\ \gamma_{i,j} &= 1 - \frac{\lambda}{(\alpha_{i,j})^2} \end{aligned}$$

The second term in (6) is independent of \mathbf{W} and thus does not effect the optimization. So the objective function to be minimized for computing the transformation matrix is given by

$$\mathbf{J}(\mathbf{W}) = \sum_{i=1}^N \sum_{j=1}^N \alpha_{i,j} (q_{i,j}(\mathbf{W}) - \beta_{i,j} d_{i,j}^h)^2 \quad (7)$$

Next we will describe the algorithm which can be used for minimization of functions of the above form.

A. Iterative Majorization Algorithm

The iterative majorization algorithm [19][20][21] is used to minimize the objective function (7) to solve for the transformation matrix \mathbf{W} . Finding the minimum of an objective function by computing its derivative and equating it to 0 is not always feasible. The central idea of the majorization method is to replace iteratively the original complicated function $\mathbf{J}(\mathbf{W})$ by an auxiliary function $g(\mathbf{W}, \mathbf{V})$. The auxiliary function, also known as the majorization function of $\mathbf{J}(\mathbf{W})$ should be simpler to minimize than the original function. It can be shown that the majorization function for $\mathbf{J}(\mathbf{W})$ is given by

$$g(\mathbf{W}, \mathbf{V}) = \text{Tr}(\mathbf{W}^T \mathbf{A} \mathbf{W}) - 2\text{Tr}(\mathbf{V}^T \mathbf{C}(\mathbf{V}) \mathbf{W}) \quad (8)$$

Here Tr denotes the matrix trace and the term \mathbf{A} is given by

$$\mathbf{A} = \sum_{i=1}^N \sum_{j=1}^N \alpha_{i,j} (\phi_i - \phi_j)(\phi_i - \phi_j)^T \quad (9)$$

The term $\mathbf{C}(\mathbf{V})$ is given by

$$\begin{aligned} \mathbf{C}(\mathbf{V}) &= \sum_i \sum_j c_{i,j}(\mathbf{V}) (\phi_i - \phi_j)(\phi_i - \phi_j)^T; \quad \text{where} \\ c_{i,j}(\mathbf{V}) &= \begin{cases} \lambda d_{i,j}^h / q_{i,j}(\mathbf{V}); & q_{i,j}(\mathbf{V}) > 0 \\ 0; & q_{i,j}(\mathbf{V}) = 0 \end{cases} \end{aligned} \quad (10)$$

One of the main features of this algorithm is that it generates a monotonically non-increasing sequence of function values. First \mathbf{W} is initialized to \mathbf{W}^0 . The different steps of the algorithm are enumerated below:

- 1) Start iteration with $t = 0$.
- 2) Set $\mathbf{V} = \mathbf{W}^t$.
- 3) Update \mathbf{W}^t to \mathbf{W}^{t+1} , where \mathbf{W}^{t+1} is the solution that minimizes the majorization function and is given by

$$\mathbf{W} = \mathbf{A}^{-1} \mathbf{C}(\mathbf{V}) \mathbf{V} \quad (11)$$

where \mathbf{A}^{-1} is the Moore-Penrose inverse of \mathbf{A} .

- 4) Check for convergence. If convergence criterion is not met, set $t = t + 1$ and go to step 2, otherwise stop the iteration and output the current \mathbf{W} .

The output of the iterative majorization algorithm is a transformation \mathbf{W} which embeds the input LR images to a new Euclidean space such that the inter-distances between them closely approximates the distances between their HR counterparts.

B. Matching

During matching, the feature vectors of both the LR probe and gallery images are first transformed using the learnt transformation matrix. If \mathbf{x}_p and \mathbf{x}_g denote the feature vectors corresponding to a probe and a gallery image, the transformed feature vectors are given by

$$\hat{\mathbf{x}}_k = \mathbf{W}^T \phi(\mathbf{x}_k) \quad (12)$$

where $k = p$ or g for probe and gallery respectively. The distances between the LR probe and gallery image is computed as the Euclidean distance between their transformed

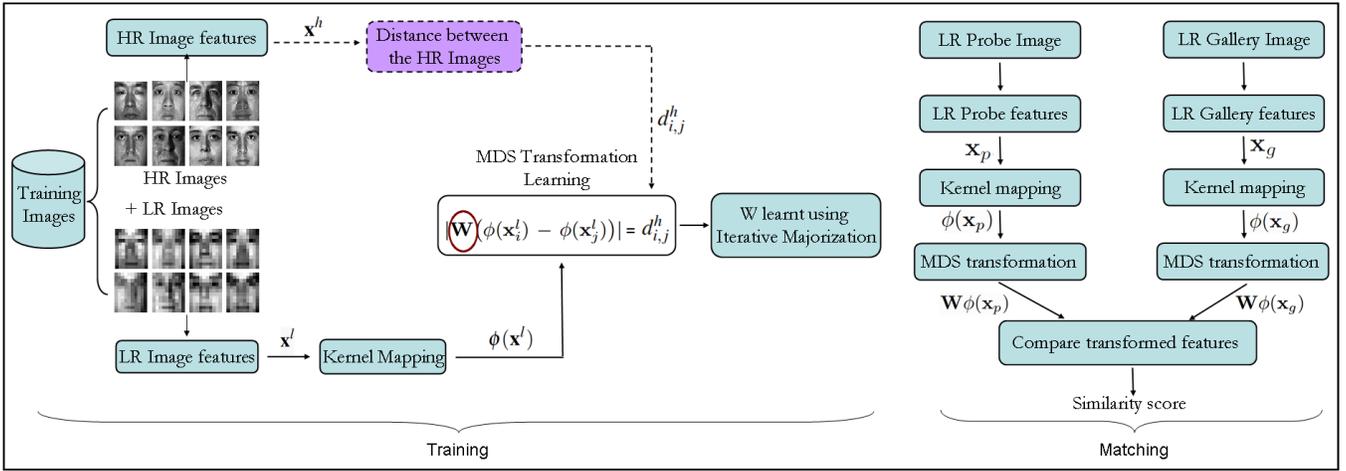


Fig. 1. Flow chart of the proposed algorithm.

feature vectors as follows

$$d = |\hat{\mathbf{x}}_g - \hat{\mathbf{x}}_p| = |\mathbf{W}^T(\phi(\mathbf{x}_g) - \phi(\mathbf{x}_p))| \quad (13)$$

Since the transformation can be learnt offline from training data, the algorithm is very fast and is suitable for databases of large size as can be expected from surveillance cameras. A flowchart of the proposed algorithm is shown in Fig. 1.

V. EXPERIMENTAL EVALUATION

In this section, we describe in details the extensive experiments performed to evaluate the usefulness of the proposed approach.

A. Implementation Details

In this paper, for the basis functions, we have used gaussian kernels of the form

$$\phi_i(\mathbf{x}) = \exp\left\{-\frac{|\mathbf{x} - \mathbf{c}_i|^2}{h^2}\right\} \quad (14)$$

where \mathbf{c}_i 's are the centers of the kernel function. In our experiments, we simply picked one image randomly of each subject from the training set and used the corresponding feature vectors as the centers. But clustering techniques like k-means, etc can also be performed on the training data to choose the centers. The value of h is typically taken as 10 in all the experiments.

For minimizing the objective function, the weights w_{ij} of the transformation matrix were initialized with random values, distributed uniformly over the range $[-1; +1]$. The two terms of the objective function in (4) are separately normalized. Specifically, the first term corresponding to the distance preserving term \mathbf{J}_{DP} is normalized by $N(N-1)$, where N is the number of training HR (or LR) images, and the second term corresponding to the class separability term \mathbf{J}_{CS} is normalized by the number of images of the same class in the training set.

For training, we require both HR and LR images of the same subject which may not be always available. In our experiments, given a HR training image, we downsample it to

generate the LR image of the same subject. We observed that the iterative optimization is quite fast and usually converges in about 20 iterations. We also observed that the performance of the proposed algorithm initially improves with increasing the output dimension and then remains almost constant for dimension greater than around 20. For all our experiments, we have used the output dimension to be 30.

In all the experiments, we have used Principal Component Analysis [22] coefficients as the feature, but any other feature can also be used. The number of PCA coefficients used to represent face images is determined based on the number of eigenvalues required to capture 98% of the total energy. We also drop coefficients corresponding to the three highest eigenvalues for robustness to illumination variations. The parameter λ is set at 0.5.

B. Comparison with different super-resolution techniques

For matching images of low resolution, the most commonly used approach is to first obtain a higher resolution image from the input using super-resolution techniques which is then used for recognition. Firstly, we compare the proposed approach with different super-resolution approaches on images from the PIE dataset [16] to show its usefulness.

This dataset contains images of 68 subjects under different illumination conditions. For this experiment, we have used 34 subjects under 6 illuminations for training and the remaining 34 subjects under the remaining illumination conditions for testing. There is no overlap between either the subjects or the illuminations between the training and testing sets. We downsampled and smoothed the input HR images and used them as the LR images. Recognition is performed across illumination with images from one illumination condition forming the gallery while images from another illumination condition forming the probe set, and the final performance is the average over all gallery and probe sets. The resolution of the HR training images was 36×30 pixels and that of the LR training, gallery and probe was 12×10 pixels. Fig. 2(a) and (b) shows examples of HR and LR images of two subjects

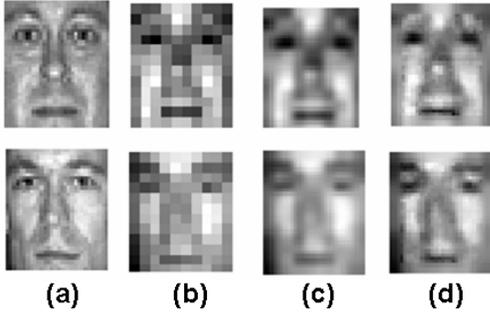


Fig. 2. Comparison with super-resolution algorithms; (a) High resolution images of size 36×30 ; (b) Corresponding LR images of size 12×10 ; (c) Output images after bicubic interpolation; (d) Output images obtained using sparse-representation based super-resolution [18].

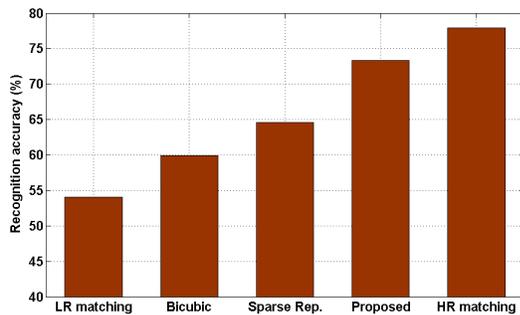


Fig. 3. Recognition performance comparison with super-resolution algorithms; (from left to right) LR matching; bicubic interpolation; super-resolution using sparse representation [18]; proposed approach and HR matching.

from the database.

First we compare the recognition performance of the proposed approach with that using the HR images using bicubic interpolation. We also compare the performance with the HR images obtained using the state-of-the-art super-resolution technique [18]. For our experiments, we have used the available code and the pre-trained dictionary, which might not have been optimally computed for face images. In this method, the different patches of the HR image are assumed to have a sparse representation with respect to an over-complete dictionary of prototype signal atoms. The principle of compressed sensing is used to correctly recover the sparse representation from the down-sampled input image. The HR reconstructed images using these two methods are shown in Fig. 2(c) and (d).

Fig. 3 shows the recognition performance. We observe that both standard LR matching and bicubic interpolation performs poorly at 54.1% and 59.8% respectively and the recognition performance using the sparse-representation based super-resolution method is 64.6%. Other authors have reported results even worse than LR matching using other super-resolution methods [4]. The proposed approach performs significantly better than all the super-resolution techniques and its performance is very close to the HR matching.

Here HR matching implies that both the probe and gallery images are of high resolution.

C. Performance analysis with varying resolution

Now we analyze the performance of the proposed learning algorithm for different resolutions of the probe and gallery images using the PIE dataset [16]. For this experiment, HR images of resolution 48×40 pixels are used for training and the resolution of the probe and gallery images are varied. We performed experiment with three different resolutions of the probe and gallery images, namely 19×16 , 12×10 and 7×6 . Fig. 4(a) shows examples of the HR training images, and Fig. 4(b),(c) and (d) shows the corresponding images for the three different resolutions in decreasing order of resolution. The performance of the proposed algorithm along with the performance of LR matching and HR matching are shown in Fig. 5. We observe that the proposed approach significantly improves the performance of LR image matching.

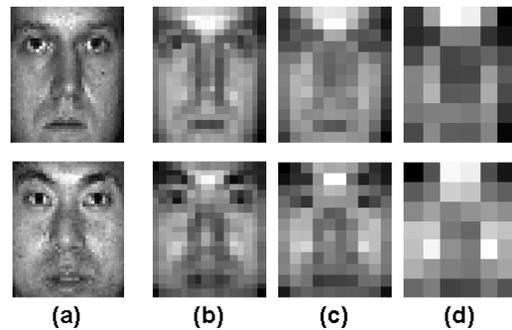


Fig. 4. Examples images of different resolution. (a) HR training images of resolution 48×40 ; Probe and gallery images of resolution (b) 19×16 pixels; (c) 12×10 pixels and (d) 7×6 pixels.

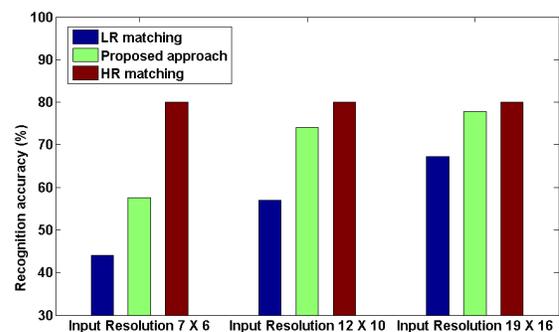


Fig. 5. Recognition performance of the proposed approach with varying gallery and probe resolutions of 7×6 , 12×10 and 19×16 respectively. Recognition performance of LR and HR matching are also shown.

D. Evaluation on the FRGC Dataset

We now evaluate the performance of the proposed approach on Experiment 1 of the FRGC dataset [23]. The dataset consists of 152 subjects with one gallery image for each subject, and 608 probe images. A separate training set



Fig. 6. Examples of images from the FRGC dataset [23] used in our experiments. The top row shows examples of HR training images at resolution 45×39 pixels and the bottom row shows LR images of the same subjects at resolution of 9×7 pixels (this is the resolution of the probe and gallery images).

with 183 images provided with the dataset is used to learn the transformation. The resolution of training images used for computing the *best distances* for learning the transformation is taken as 45×39 pixels and the resolution of the probe and gallery images are 9×7 pixels. Some images from the FRGC dataset at the high training resolution and low probe and gallery resolutions are shown in Fig. 6. Fig. 7 shows the Cumulative Match Characteristic (CMC) curve obtained. We see that even on this data, the proposed approach significantly improves the performance of matching the LR input images.

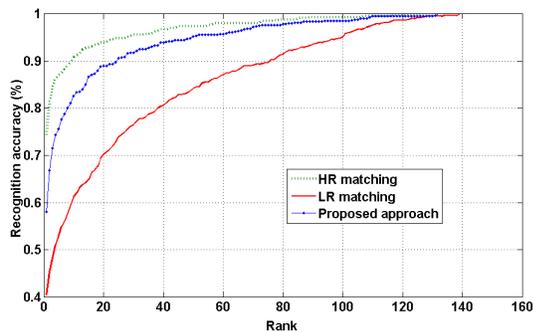


Fig. 7. Recognition performance on the FRGC dataset [23]. The performance of LR and HR matching are also shown for comparison.

VI. SUMMARY AND CONCLUSIONS

In this paper, we proposed a novel approach for improving the recognition performance of poor resolution images as usually obtained from surveillance cameras using MDS. The main idea is to learn a transformation of the low resolution images such that the distance between them approximates the *best distances* had these images been of good resolution. This mapping is learnt using iterative majorization technique from HR training images and corresponding LR images of the same subject. Extensive experimental evaluation shows the usefulness of the proposed approach. Though all the experiments have been performed on facial images, the proposed approach is very general and can be applied to any domain where such learning is feasible.

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