Very Low Resolution Face Recognition Problem

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Abstract

This paper addresses the very low resolution (VLR) problem in face recognition in which the resolution of face image to be recognized is lower than 10x10. The VLR problem happens in many surveillance camera-based applications and existing face recognition algorithms are not able to give satisfactory performance on VLR face image. While face super-resolution (SR) methods can be employed to reconstruct a higher resolution image, the existing face SR methods do not perform well on such a low resolution. Unlike the existing SR methods working on VLR input image space, this paper proposes a new data constraint which performs error measurement in high resolution (HR) image space. As HR image contains detailed and discriminative information, the reconstructed HR image gives both better visual quality and recognition performance. Moreover, with the use of new data constraint, discriminative constraint can be easily integrated in the optimization process. CMU-PIE and FRGC face databases are selected for experiments. Experimental results show that the proposed method outperforms existing methods.

1. Introduction

With the growing installation of surveillance cameras in public areas, ranging from a small-scale stand-alone camera applications in banks and supermarkets to large-scale multiple networked-close-circuit television (CCTV) in law enforcement applications in public streets, there is an increasing demand of face recognition technology for surveillance cameras. Wide-angle cameras are normally used and installed in a way that viewing area is maximized. In turn, face region in the scene is normally very small. When the person is not close to the camera, the face region will be less than a hundred of pixels (i.e., smaller than 10x10 pixels) as shown in Figure 1. Recognition of such a very low-resolution face image called very low-resolution (VLR) face recognition problem. While face recognition research has been studying for more than three decades and many promising practical face recognition systems have been developed, it is assumed the face region is large enough and

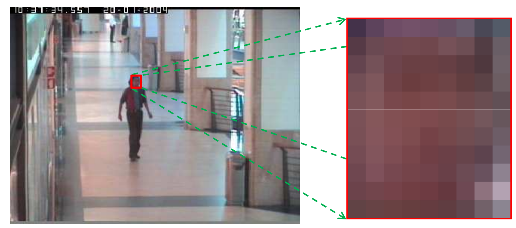

Figure 1. A typical frame from a surveillance video (from CAVIAR database)

contains sufficient information for recognition [20]. Empirical studies [11] showed that minimum face image resolution between 32x32 and 64x64 is required for existing algorithms. The recognition performance of the existing methods on VLR face image will degrade dramatically. This is because the VLR face image contains very limited information and many image details have been lost in the downsampling process as shown in Figure 1(b). It can be seen that even human is hard to recognize the face image.

Super-resolution (SR) is a method to construct a high-resolution (HR) image from its low-resolution (LR) image [3, 16, 13]. Theoretically, applying SR technique on VLR face image, the reconstructed HR image can be used for face recognition. However, existing face SR algorithms do not give satisfactory results on VLR face image.

Most, if not all, of the existing face SR algorithms are learning-based (please refer to section 2 for details) and formulated as a constraint optimization problem. Generally speaking, two types of constraints namely, data constraint and algorithm specific constraint, are considered. To the best of our knowledge, all existing algorithms employed the same data constraint, which is defined as

$$\|D\tilde{I}_h - I_l\|^2 \tag{1}$$

where $\tilde{I}_h$ and I_l represent the reconstructed HR face image and the input VLR face image , D is the downsampling matrix. The objective of data constraint is to find a HR image such that the downsampled reconstructed HR image is very close to the input VLR face image. It can be seen that the data constraint measures the error in input low dimen-

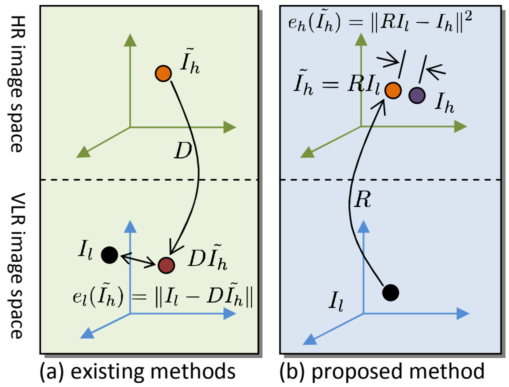

Figure 2. Data constraint in existing methods vs. the proposed data constraint

sional image space as illustrated in Figure 2(a). In VLR face recognition problem, the VLR image dimension is too small to reflect the error in high dimensional space. The contribution of the data constraint is not significant and the algorithm specific constraint will dominate the optimization process (please refer section 3 for details). In turn, the reconstructed HR image may not be similar with the input image.

To overcome the VLR problem, this paper proposes a new formulation of the data constraint. Unlike existing methods performing the error measurement in VLR image space, this paper proposes to perform the measure in HR image space as illustrated in Figure 2(b). To achieve this, this paper develops a new learning procedure to determine the relationship R between the VLR space and HR image space. It is noted that the VLR and HR image pairs (I_l, I_h) are available in training stage. Moreover, with the use of the new data constraint, discriminative term can also be easily integrated into the optimization process. In turn, the reconstructed HR image using the proposed method not only has high visual quality, but also has high discriminability for recognition.

The rest of this paper is organized as follows. Section 2 gives a brief review on the existing face super-resolution algorithms. Section 3 discusses the limitation on current data constraint used in existing methods. The proposed method and experimental results are reported in Section 4 and Section 5, respectively. Finally, Section 6 draws the conclusion.

2. Related Work

With the prior information that the image to be super-resolved is a human face, most, if not all, existing face SR algorithms (face hallucination [1]) are learning based. Let I_h and I_l be the HR image and input LR image, respectively. The objective of SR is to determine a high resolution image $\tilde{I}_h$, given the input VLR image and a downsampling matrix D, by solving the following equation,

$$D\tilde{I}_h = I_l \tag{2}$$

Since D is an N-to-one mapping, solving Eq.2 is ill-posed. To overcome the problem, many learning-based face SR algorithms [1, 2, 4, 5, 6, 7, 9, 10, 17, 19, 12] have been developed. We categorize the algorithms into two approaches namely, example based and maximum a posterior (MAP) based.

In MAP-based approach, different constraints, which are induced from the conditional probability $P(I_h|I_l)$, are used to alleviate the ill-posed problem. Eq.(2) is converted to maximize the conditional probability $P(I_h|I_l)$ and in turn, maximize $P(I_h|I_l) * P(I_h)/P(I_l)$. To do this, the key step is to model $P(I_h)$ so that it can restrict the reconstructed HR image belonging to the HR face image space. Some researchers model $P(I_h)$ by non-parameter density estimation. Baker *et al.* [1] considered the distance between the LR input image patch and the most similar training image patch to estimate $P(I_h)$. Liu *et al.* [9] employed non-parameter Markov network to model the HR residual images which is useful to recover the HR image with good visual quality. Subspace method is also employed to restrict the reconstructed HR image locating inside the face subspace, such as PCA subspace [9] and KPCA subspace [2]. They estimated $P(I_h)$ by minimizing the reconstructed mean squared error.

In example-based approach, the HR image is reconstructed by restricting in the face subspace spanning by the HR examples. Denote $I_l = a_1 I_l^1 + a_2 I_l^2 + \cdots + a_n I_l^n$, where a_i and I_l^i are the weight (coefficient) and LR image example, respectively, $i = 1 \cdots n$. The reconstructed HR image I_h can be obtained by replacing the LR examples (I_l^i) by the corresponding HR examples (I_h^i), i.e., $I_h = a_1 I_h^1 + a_2 I_h^2 + \cdots + a_n I_h^n$. This approach assumes that the structure in LR subspace is the same as that in HR subspace. Based on this idea, Wang *et al.* [18] proposed an algorithm using Eigen-transformation while Zhang *et al.* [19] performed on DCT domain. Liu *et al.* [10] and Jia *et al.* [6] conducted in patch tensor space while Park *et al.* [12] conducted on face texture space and face 3D shape space. The assumption, which the structure in LR subspace is the same as that in HR subspace, may not be valid due to the face variance. In turn, the performance may not be satisfactory on face image with variations.

Moreover, a few methods were developed from recognition perspective. Gunturk *et al.* [4] applied MAP-based SR method to reconstruct the eigenface coefficients for face recognition. Hennings-Yeomans *et al.* [5] proposed to perform SR and feature extraction from LR image simultaneously. Wang *et al.* [17] employed example-based approach to reconstructed HR images for face recognition, while Li *et al.* [7] reconstructed the image features, instead of HR images, for face recognition.

3. Limitation on Current Data Constraint

From the review in Section 2, existing super-resolution methods can be generalized and formulated as 2-constraint optimization problem,

$$\tilde{I_h} = \arg\min_{I_h} \varphi_D(I_h) + \varphi_S(I_h) \tag{3}$$

where $\varphi_D(.)$ is the data constraint and $\varphi_S(.)$ is the algorithm specific constraint. Both MAP-based and example-based approaches use the same data constraint

$$\varphi_D(I_h) = \|D\tilde{I_h} - I_l\|^2 \tag{4}$$

MAP-based approach employs $\|D\tilde{I_h} - I_l\|^2$ which is induced from the condition probability $P(I_l|I_h)$. Example-based methods use the data constraint implicitly. It minimizes the difference defined as follows

$$\{\tilde{a_i}\} = \arg\min_{\{a_i\}} \|I_l - \sum a_i I_l^i\|^2 \tag{5}$$

to get the weights for HR examples to reconstruct the HR image. Considering $DI_h^i = I_l^i$, this difference is the data constraint in Eq.(1).

Let the solution space (set) of equation e is $\mathbf{U}(e)$. It can be shown that the solution of Eq.(3), $\tilde{I_h}$, locates in the intersection of the two constraints' solution space, as follows:

$$\{\tilde{I_h}\} = \mathbf{U}(\varphi_D \le c_1) \cap \mathbf{U}(\varphi_S \le c_2) \tag{6}$$

where c_1 and c_2 are two positive error terms (constants) to control the dimension (size) of the solution space. The smaller the term is, the smaller the dimension of the solution space.

Under the VLR face recognition problem, even though c_1 is set to 0, the solution space $\mathbf{U}(\varphi_D = 0)$ is still very large. This can be explained by considering the following example. Suppose the resolution of the input image is 8 x 8 and the target HR image with resolution of 64 x 64. From linear algebra, the dimension of the solution space of $\mathbf{U}(\varphi_D = 0)$ is not less than 4032 (= 64x64 - 8x8), while the dimension of the target HR image space is 4096. In another word, $\mathbf{U}(\varphi_D = 0)$ occupies 98.44% of that in HR image space. It means that data constraint cannot effectively restrict the target HR image solution space. Therefore, in determining the high resolution image, the algorithm specific constraint $\mathbf{U}(\varphi_s \le c_2)$ will dominate during the optimization process. In turn, there is a possibility that reconstructed HR image may have serious artifacts and/or not look like the original person.

4. Proposed Relationship Learning based Super-resolution

To overcome the limitation on current data constraint, this paper proposes a new formulation of the data constraint which measures the error in HR image space. As illustrated in Figure 2(b), the basic idea is to determine the relationship, R, between the VLR image space and HR image space, which is represented in the form of matrix. Unlike the current data constraint shown in Figure 2(a), the proposed new data constraint minimizes the error in HR image space. Since HR image space contains more useful and detailed image information, the reconstructed image will have a higher visual quality and contains more discriminative information. The detailed method in determining the relationship R will be given in Section 4.1. Another advantage of the proposed method is that other constraint(s) can be easily integrated into the new data constraint while determining R. To demonstrate this superior property, this paper adapts a simple discriminative constraint and integrates into the new data constraint. Details will be given in Section 4.2.

4.1. Relationship Learning (RL)

Under the VLR problem, the input VLR image space contains very little useful information, so current data constraint does not estimate the reconstruction error well. A reasonable method is to estimate such error in HR image space. But the challenge is that given a VLR query image, the corresponding HR image is not available. Instead of learning the HR image directly, we propose a new SR framework to learn the relationship between HR image space and LR image space. After determining the relationship R, HR image can be reconstructed by R.

Given a set of training HR and VLR image pairs $(\{I_h^i, I_l^i\}_{i=1}^N)$, and let R be the relationship between the HR image space and the VLR image space. The HR image can be reconstructed from its VLR image and R, by $\tilde{I_h} = RI_l$. So the reconstructed error in HR image space, $e_h(\tilde{I_h})$, is given by,

$$e_h(\tilde{I_h}) = \|I_h - RI_l\|^2 \tag{7}$$

R can then be determined in training stage by minimizing this error as follows

$$R = \arg\min_{R'} \sum_{i=1}^{N} \|I_h^i - R' I_l^i\|^2 \tag{8}$$

It can be shown that R is unique if the number of training image pairs N is larger than the data dimension of VLR image space d_L. $N > d_L$ is true in many VLR face recognition applications.

In query stage, given a query VLR image I_l, the corresponding HR image is recovered as follows,

$$\tilde{I_h} = RI_l \tag{9}$$

In this paper, this method is called relationship learning (RL) super-resolution.

4.1.1 Error Analysis

Considering that a HR image I_h consists of two components namely, the low frequent image component l and high frequent image details h; and they satisfy $Dh = 0$ and $Dl = l$. The HR image can then be represented as

$$I_h = l + h \tag{10}$$

The reconstruction error can also be separated into two parts namely, low frequent image component error Δl and high frequent details error Δh. So the reconstructed HR $\tilde{I_h}$ is given by,

$$\tilde{I_h} = I_h + \Delta l + \Delta h \tag{11}$$

For the current data constraint used in existing methods, the error is formulated as

$$\begin{aligned} e_l(\tilde{I_h}) &= \|D\tilde{I_h} - I_l\|^2 = \|D(I_h + \Delta l + \Delta h) - I_l\|^2 \\ &= \|\Delta l\|^2 \end{aligned} \tag{12}$$

so $e_l(\tilde{I_h})$ reflects the error introduced by low frequent image component only. For our proposed method, we have

$$\begin{aligned} e_h(\tilde{I_h}) &= \|\tilde{I_h} - I_h\|^2 = \|I_h + \Delta l + \Delta h - I_h\|^2 \\ &= \|\Delta l + \Delta h\|^2 \end{aligned} \tag{13}$$

That means our proposed method can estimate the reconstruction error from both low frequent image component l and the high frequent details h.

In turn, both Δh and Δl will be minimized when $e_h(\tilde{I_h})$ is minimized, while minimizing $e_l(\tilde{I_h})$ only leads Δl is minimized.

From the discussion in Section 3, in VLR face recognition problem, it can be shown that the reconstructed HR image $\tilde{I_h}$ easily satisfies

$$\|\Delta l\|^2 = 0 \tag{14}$$

due to the large solution space of $\mathbf{U}(\|D\tilde{I_h} - I_l\|^2 = 0)$. This implies that the major reconstructed error is caused by $\|\Delta h\|^2$. To get better HR image quality, error caused by both Δl and Δh should be minimized. Our proposed data constraint can properly estimate the reconstructed error. In turn, the proposed SR algorithm could make use of more useful information in the HR image space, and recover the high frequent details of face image better.

4.2. Discriminative Constraint

It can be seen that R restricts the reconstructed HR images locating in an optimal subspace for minimizing the reconstruction error $e_h(\tilde{I_h})$. This inspires us to find an optimal subspace induced by R with other additional constraint(s). In order to further boost the discriminability of the reconstructed HR image, discriminative constraint is added to the relationship learning based SR in determining the "optimal" R. A discriminative super-resolution (DSR) algorithm is proposed.

A natural step is to make use of the class information of the training data. From recognition perspective, we expect the reconstructed HR images should be clustered with the images from the same class, and far away from the images from other classes. Therefore, based on maximum margin criterion (MMC) [8], we design a discriminative constraint as follows:

$$\begin{aligned} d(R) = &\frac{1}{N_1} \sum_{\Omega(I_h^i)=\Omega(I_l^j)} \|I_h^i - RI_l^j\|^2 \\ &- \frac{1}{N_2} \sum_{\Omega(I_h^i)\neq\Omega(I_l^j)} \|I_h^i - RI_l^j\|^2 \end{aligned} \tag{15}$$

where N_1, N_2 are normalization constants, and $\Omega(u)$ is the class label of u. Integrating Eq.(15) with Eq.(8), the new discriminative super resolution formula can be written as :

$$\dot{R} = \arg\min_{R'} \frac{1}{N} \sum_{i=1}^{N} \|I_h^i - R' I_l^i\|^2 + d(R') \tag{16}$$

And the HR image can be reconstructed by $\dot{R}$.

This subspace induced by $\dot{R}$ is an optimal subspace for recognition with respect to MMC. That means the HR images reconstructed by $\dot{R}$ locates in a subspace where they can be linear separable. Therefore, the HR image reconstructed by $\dot{R}$ will contain more discriminability and better for recognition purpose.

5. Experiments and Analysis

Two experimental results are reported in this section. In the first experiment, we would like to evaluate the reconstructed HR image quality using the proposed method. Both objective measurement in terms of mean squared error (MSE) and subjective human visual quality are used. Comparison with existing face SR methods are also reported. The second experiment is to evaluate the reconstructed HR image discriminability using the proposed method. Three popular face recognition methods namely eigenface, kernel PCA and SVM, are selected as recognition engine. Recognition results on HR images reconstructed using existing SR methods are also reported.

Two public databases namely, CMU PIE [15] and FRGC 2.0 [14] are used for experiments. For CMU PIE database, a subset of 68 classes with 21 different illuminations is considered. For FRGC database, the subset of 311 classes with 10 images per class is used. In all experiments, the resolution of VLR image is 7x6 while the resolution of HR image is 56x48. The magnification is 8, which is challenging in SR. To determine the relationship matrix R and train the recognition engine, 13 and 8, HR and VLR image pairs from each person are randomly selected from CMU PIE and FRGC databases for training, respectively, while the rest are used for testing.

Three existing face SR methods namely Hallucination Face (HF) method [1], Eigentransfromation based Face SR (EF) method [18] and KPCA-based Face SR (KF) method [2] are selected for comparison. The results of BiCubic interpolation (BC) are also given for benchmarking.

5.1. Experiment 1: Image Quality

Figure 3 shows some of the reconstructed images using proposed method and existing methods. Figures 3(a) and (g) show the input 7x6 query image and original 56x48 HR image. Figures 3 (b) - (e) display the results using bicubic interpolation method, HF [1] method, EF [18] method and KF [2] method. It can be seen that both bicubic interpolation (BC) method and KF method give a relatively blur image and high frequency details cannot be recovered. Both HF method and EF method could recover some high frequent details. However, HF method generates some artifacts which degrade the human visual quality. The visual quality of reconstructed HR images from EF method are good. However, when comparing with the original HR image, the reconstructed HR image does not look like the original HR image. Figure 3(f) shows the results using our proposed method. It can be seen that the proposed method gives a good visual quality image which also look like the original one.

To further evaluate the SR algorithms in terms of the visual quality, the zoom-in results are given in Figure 4. For each image shown in Figure 4 (a), the first row shows the zoom-in result while the second row shows the downsampled VLR images. It can be seen that both HF method and EF method introduce server artifacts. At the same time, if we look at the VLR images, the artifacts can not be reflected at VLR images. This supports the analysis in Section 4.1.1. The results using our proposed method are shown in Figure 4(e). It can be seen that the results are good.

The mean squared error (MSE) of the proposed method and the existing methods on two databases are also recorded and shown in Table 1. The error reported in the table is the average of the all testing images. It can be seen that for both databases, the proposed method gives the smallest MSE.

5.2. Experiment 2: Image Discriminability

In this experiment, we would like to evaluate the performance of the discriminative super resolution (DSR) algorithm in terms of the recognition result. Recognition experiments are performed on (i) input VLR query images, (ii) original HR images, reconstructed HR images from (iii) HF [1], (iv) EF [18], (v) KF [2] and (vi) the proposed DSR method. Three face recognition engines namely eigenface, KPCA and SVM, are used for experiments on CMU PIE and FRGC databases. The results are recorded in Table 2. Experimental results show that:

- There is a significant drop of recognition accuracy (as high as 30%) for VLR image, comparing with the original HR image, for all recognition engines on both databases.
- The proposed method outperforms existing SR methods. It implies that the reconstructed HR image using the proposed method has high discriminability for recognition purpose.

The CMC curves are also plotted from Figures 5 - 7 for CMU PIE database and Figure 8-10 for FRGC database.

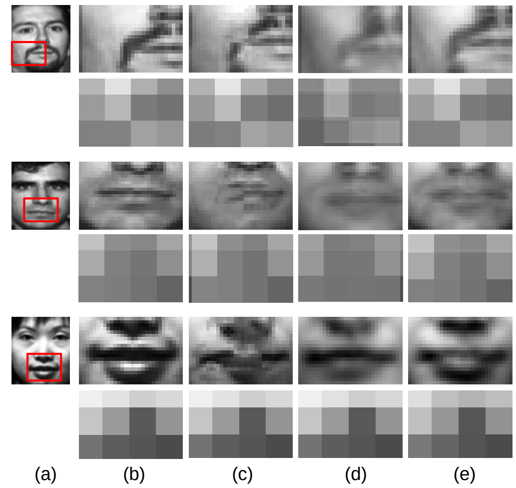

Figure 4. The zoom-in results of different SR algorithms. (a) and (b) are original HR images, (c) Hallucination Face method (HF)[1], (d) Eigentransfromation based Face SR method (EF) [18], (e) proposed RL method.

6. Conclusion

The very low resolution face recognition problem is defined and discussed in this paper. To solve the problem, a new super-resolution method has been developed. A new data constraint for super-resolution has been designed and reported. The proposed new data constraint offers at least two advantages. First, the error is measured in high resolution image space so that better high resolution image quality image can be obtained. Second, with the use of new data constraint, discriminative constraint can be easily integrated. Moreover, based on the new data constraint, a new learning based super-resolution approach which learns the relationship between low resolution image space and high resolution image space, is also proposed.

Database	BC	HF [1]	EF [18]	KF [2]	Proposed RL
CMU PIE	424.4	475.6	291.9	1143.1	179.9
FRGC 2.0	1259.4	1838.8	1510.1	1707.6	870.5

Table 1. The MSE of different SR methods (Average of all testing images)

Figure 3. SR results: (a)input VLR images (7 x 6), (b) SR results by Bicubic interpolation,(c) by Hallucination Face method (HF)[1], (d) Eigentransfromation based Face SR method (EF) [18], (e) KPCA-based Face SR method (KF) [2], (f) Our proposed method (RL), (g) original HR images. The resolution of reconstructed HR images is 56 x 48.

CMU PIE and FRGC databases are selected for experiments and the results show that the proposed method not only gives better visual image quality, but also smaller mean squared error, comparing with existing face super-resolution methods. Three face recognition algorithms are also selected to evaluate the discriminability of the reconstructed high resolution images. Experimental results show that the reconstructed images using the proposed method outperforms those reconstructed from existing face super-resolution methods. This illustrates that the reconstructed high resolution has high discriminability as well.

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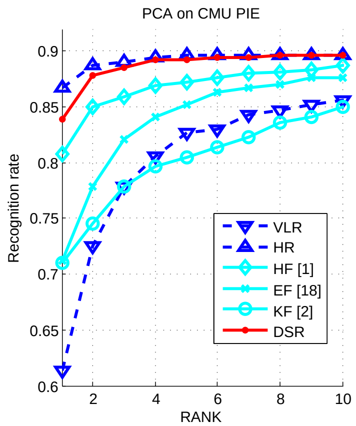

Figure 5. Eigenface on CMU PIE

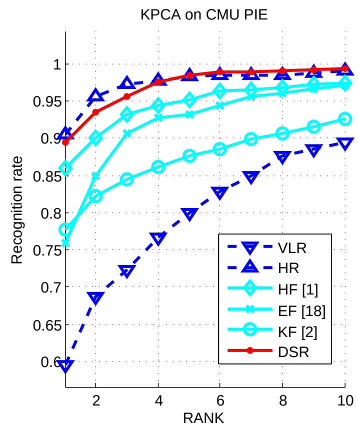

Figure 6. Kernel PCA on CMU PIE

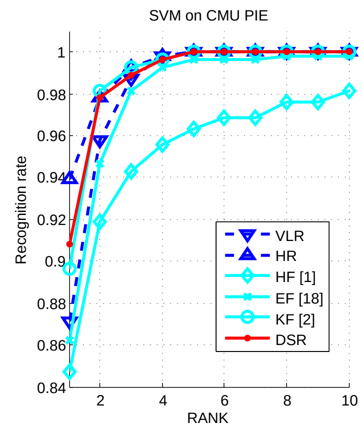

Figure 7. SVM on CMU PIE

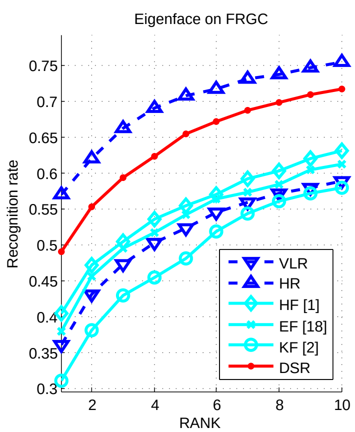

Figure 8. Eigenface on FRGC

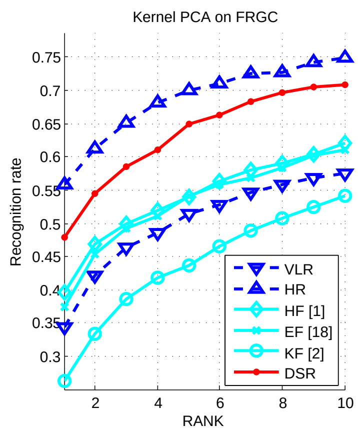

Figure 9. Kernel PCA on FRGC

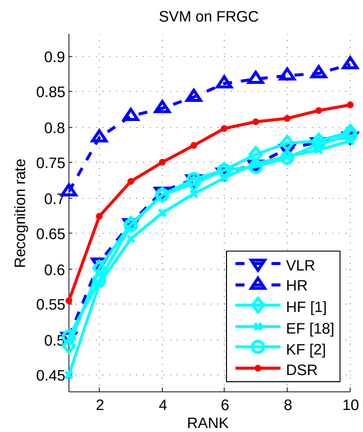

Figure 10. SVM on FRGC

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Database	face recognition algorithm	very low resolution image	original high resolution image	HF [1]	EF [18]	KF [2]	Proposed DSR
CMU PIE	Eigenface	61.3	86.7	80.8	71.3	71.7	**83.9**
	Kernel PCA	59.5	90.4	86.0	75.9	77.8	**89.5**
	SVM	87.1	93.9	84.7	86.2	89.6	**90.8**
FRGC 2.0	Eigenface	36.0	57.1	40.5	37.9	31.1	**49.0**
	Kernel PCA	34.4	55.8	39.6	37.5	26.4	**47.9**
	SVM	50.4	70.9	49.2	45.0	50.4	**55.5**

Table 2. Rank 1 recognition rate (%).

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