Adaptive Feature Transformation for Classification with Sparse Representation

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Abstract—Sparse representation based classification (SRC) has been shown to be an effective method for face recognition. Furthermore, the input features of more and more classifiers are extracted by dimensional reduction methods. However, we find that the reconstruction ability of a basis for a testing sample is related with cosine distance between this basis and this testing sample, but most dimensional reduction methods are based on Euclidean distance. Obviously, a gap is existed between dimensional reduction methods and SRC. In this paper, we propose an adaptive feature transformation based on self-tuning point to point distances (SPPDAFT) to transform features to a new feature space. The SPPDAFT can makes that the cosine distances among samples in new feature space increase with the Euclidean distances among samples in original space. As a result, the reconstruction ability of a basis to a testing sample in new feature space would be indirectly related with the Euclidean distance between this basis and this sample in original space, and then the gap between dimensional reduction methods and SRC can be reduced. The experimental results on benchmark databases show the effectiveness of SPPDAFT.

Index Terms—Sparse Representation Classification, Dimensional Reduction, Feature Transformation, Face Recognition

I. Introduction

Sparse representation has recently been applied to a variety of applications in computer vision and machine learning [1-5]. Its success is attributed to the fact that the dimensionality of signals such as natural images is often much lower than that which is observed, and thus it offers a more compact yet better description of natural signals for the above applications[4]. To extend sparse representation to the problems of classification, Wright [36] proposed sparse representation based classification (SRC), which obtains good results on face recognition.

However, there are three defects for SRC. Firstly, due to the over complete codebook and the independent coding process, the locality and the similarity among the samples are lost [17~23]. Secondly, using original training samples as the dictionary cannot fully exploit the discriminative information hidden in the training samples [9-13]. Thirdly, dimensional reduction methods are often used to extracted features for SRC [8,11,26,27,30,36], however, a gap is existed between these dimensional reduction methods and SRC, because the goal of most dimensional reduction methods is maximizing the Euclidean distances across classes and minimizing the

Euclidean distances within the class, while the reconstruction ability of each basis for a testing sample is related on the cosine distances between this basis and this sample.

To overcome the first defect, some optimization problems for sparsely coding have been proposed [14,17-18, 20-23]. These methods think that the locality among the coefficients of samples should be the same as the locality among these samples, and add an item in optimization problems to keep above relationship. Obviously, the reconstruction ability of each basis does not be changed.

To overcome the second defect, some dictionary learning methods have been proposed. Jiang[9] introduces a new label consistent KSVD (LCKSVD), which learns a single over complete dictionary, a linear transformation matrix, and an optimal linear classifier jointly. However, the transformation matrix is learned for sparse coefficients but not for the bases, so that the reconstruction ability of each basis does not be changed. Chen [12] proposes a discriminative low-rank representation (DLRR), which makes the dictionary elements between different classes as independent as possible. However, DLRR minimizes the reconstruction errors between dictionary and training data, and then the variances of the reconstruction abilities of bases are very small. Yang [13] proposed a fisher discrimination dictionary learning (FDDL) approach for sparse representation classification. However, the test samples without any transformation, and then the learned dictionary may be not suitable to testing samples.

To overcome the third defect, three methods can be used: (1) the input features of SRC can be mapped to a kernel space [6, 7], however, a suitable kernel is hardly chosen. (2) Setting different weights for the sparse coefficients [15, 19, 26-28], however, the reconstruction abilities of bases also does not be changed. Thirdly, using sparse representation based dimensional reduction methods [16,29-32]. Can-Yi Lu [29] proposed optimized projections for SRC (OP-SRC), it aims to reduce the within-class reconstruction residual and increase the across-class reconstruction residual, however, the reconstruction residual are computed from high dimensional space, and then the reconstruction residual would not be keep in low dimensional space. Jie Gui[30] proposed discriminant sparse neighborhood preserving embedding (DSNPE), it preserves the sparse reconstructive relationship among the samples and sufficiently utilizes the global discriminant structures, however, the define of discriminant structures is also based on Euclidean distances, and then a gap is also existed.

In this paper, we propose an adaptive feature transformation

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based on self-tuning point to point distances (SPPDAFT) to overcome the third defect. SPPDAFT transforms the features to a new feature space, and makes that the cosine distances among samples in new feature space increase with the Euclidean distances among samples in original space. As a result, the reconstruction ability of a basis to a testing sample in new feature space would relate with the Euclidean distance between this basis and this sample in original space, and then the SRC can fully utilize the information extracted by dimensional reductions methods, which means that the third defect of SRC can be overcome. Obviously, if the features extracted by dimensional reduction contain the discriminative information, the dictionary in new feature space also contains discriminative information, and then the second defect of SRC can be overcome. Furthermore, because the reconstruction ability of a basis to a testing sample relate with the cosine distance between this basis and this testing sample, so that two testing samples with a small cosine distance would have similar cosine relationships with bases, and then the first defect of SRC is also overcome.

The remainder of this paper is organized as follows. Section 2 introduces the related work. Section 3 introduces the proposed SPPDAFT and describes how SPPDAFT performed with SRC. Experimental results are presented and discussed in Section 4. Finally, Section 5 gives concluding remarks.

II. Related Work

The proposed SPPDAFT is used to reduce the gap between the supervised or semi-supervised dimensional reduction and SRC, so that in this section we first review SRC, and then review supervised or semi-supervised dimensional reduction.

A. Sparse representation based classification (SRC)

Wright *et al* [36] proposed the sparse representation based classification (SRC) for robust face recognition. Suppose that we have c classes, and let $D = [D_1, D_2, \dots, D_c]$ be the set of original training samples, where D_c is the sub-set of the training samples from class c . Denote by x a testing sample. The procedures of SRC are as follows.

- (1) Sparsely code x on D via l_1 -norm minimization

$$\hat{\alpha} = \arg \min_{\alpha} \|x - D\alpha\|_2^2 + \lambda \|\alpha\|_1 \quad (1)$$

Where λ is a scalar constant, $\|x - D\alpha\|_2^2$ is used to computed the reconstruction error, and $\|\alpha\|_1$ is used to keep sparse of α

- (2) Compute reconstruction error for each class

$$E_c = \|x - D_c \hat{\alpha}_c\|_2^2 \quad (2)$$

- (3) Do classification via

$$\hat{c} = \text{SRC}(x) = \arg \min_c E_c \quad (3)$$

B. Kernel Sparse representation based classification (KSRC)

Suppose that we have the training samples $X = [x_1, x_2, \dots, x_n]$ and a testing sample x , the procedures of KSRC are as follows.

- (1) Select a Mercer kernel $k(\cdot, \cdot)$. Where the linear kernel is presented by Eq.(4) and the RBF kernel is presented by Eq.(5), where γ is the parameter of RBF kernel.

$$k(x_i, x_j) = x_i^T x_j \quad (4)$$

$$k(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|_2^2) \quad (5)$$

- (2) Compute the kernel Gram matrix K ,

where $K_{ij} = k(x_i, x_j)$, and $k(\cdot, x) = [k(x_1, x), \dots, k(x_n, x)]^T$.

- (3) Normalize the columns of K and $k(\cdot, x)$ to have unit l_2 -norm.

- (4) Set $D = K$, $x = k(\cdot, x)$, and use Eq.(1) to (3) to get the class label of x .

C. Supervised or semi-supervised dimensional reduction

Recently, a large number of dimensional reduction methods can be used to map features from high dimensional space to low dimensional space, such as: Principal Component Analysis (PCA) [45], Linear Discriminant Analysis (LDA) [45], Neighborhood Preserving Embedding (NPE) [37], and some semi-supervised dimension reduction methods [38-44]. Most of supervised or semi-supervised dimension reduction methods have the following framework:

$$W^* = \arg \max_{W^T W = I} \frac{\lambda_1 W^T S_b W + \lambda_2 W^T S_f W}{\lambda_3 W^T S_w W + \lambda_4 W^T S_m W} \quad (6)$$

Where W is a mapping matrix, which is used to map the feature from high dimensional space to low dimensional space; S_b, S_w, S_f, L^M are used to define the relationships among training points; and $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are scalar constants.

From the principle of most supervised or semi-supervised dimensional reduction [37-45], constructing S_b, S_w, S_f, L^M is based on Euclidean distance, so that the classifier that can utilize the advantage of these supervised or semi-dimensional reduction methods should be also based on Euclidean distance. However, in SRC, the reconstruction ability of bases are not changed with Euclidean distances.

III. Adaptive Feature Transformation for Classification with Sparse Representation

We now detail our proposed algorithm. In the first subsection, we will introduce the motive of SPPDAFT. In the second subsection, we will give the proposed SPPDAFT. In the third subsection, we will give how SPPDAFT is used with SRC. And in the last subsection, we compare the SPPDAFT with some related algorithms.

A. Motive

Many algorithms can be used to solve l_1 -norm minimization problem, such as: Least Angle Regression (LARs) [33], Gradient Projection for Sparse Reconstruction (GPSR) [34], and so on. From these algorithms, we find that the reconstruction ability of a basis to a testing sample is greatly influenced by the cosine distance between this basis and this sample. However, the goal of most dimensional reduction methods is maximizing the Euclidean distances across classes and minimizing the Euclidean distances within class. As a result, a gap is existed between SRC and most dimensional reduction methods, which can be shown by an example. The example is presented on Fig.1.

Fig.1 An example used to show the gap between dimensional reduction and SRC. (a) Sparse coefficients of bases to a testing sample, (b) cosine distances between bases and this testing sample, (c) Euclidean distances between bases and there testing sample, where 12 green bases are with small Euclidean distances to the testing sample, and 12 red bases are with samll cosine distances to the testing sample.

It can be seen from Fig.1 that the coefficients of 12 red bases are all very large, but most of coefficients of 12 green bases are very small, obviously, the reconstruction ability of bases in this example are more related with cosine distances than with Euclidean distances.

Some people think that normalized the samples with length 1, the cosine distances can increase with Euclidean distances, and then the gap can be eliminated. However, we all know that normalized the samples with length 1 not changes the cosine distances among samples but changes the Euclidean distances among samples, and then it would disrupt the discriminative information extracted by dimensional reduction. In this paper, we design a feature transformation named SPPDAFT to reduce the gap between the dimensional reduction and SRC.

B. SPPDAFT

Given n training samples $X = [x_1, x_2, \dots, x_n] \in \mathbb{R}^{m \times n}$, and a testing sample $x \in \mathbb{R}^m$, where m is the dimension of the sample, n is the number of the training samples. The SPPDAFT $x_i \in \mathbb{R}^m \rightarrow y_i \in \mathbb{R}^n$ for a training sample can be defined as:

$$y_i = [d_s(x_i, x_1), d_s(x_i, x_2), \dots, d_s(x_i, x_n)]^T \quad (7)$$

The SPPDAFT $x_i \in \mathbb{R}^m \rightarrow y_i \in \mathbb{R}^n$ for a training sample can be defined as:

$$y = [d_s(x, x_1), d_s(x, x_2), \dots, d_s(x, x_n)]^T \quad (8)$$

Where $d_s(x_i, x_j)$ is defined as:

$$d_s(x_i, x_j) = \exp(-w_{ij}^2), \quad w_{ij} = \sqrt{d_E^2(x_i, x_j) / \sigma_i \sigma_j} \quad (9)$$

Where $\sigma_i = d_E(x_i, x_i^k)$ and $\sigma_j = d_E(x_j, x_j^k)$ are two local scale parameters, x_i^k and x_j^k are the k -th neighbor of x_i and x_j , and $d_E(x_i, x_j)$ is the Euclidean distance between x_i and x_j . It can be seen from Eq.(7) and (8) that SPPDAFT transforms the features to a new feature space, where the j -th feature of y_i is $d_s(x_i, x_j)$. To describe simply, $\mathbb{R}^m$ is marked as low dimension space and $\mathbb{R}^n$ is marked as SPPD space.

Obviously, if cosine distances in SPPD space can increase with the Euclidean distances in low dimension space, the gap between dimensional reduction and SRC can be reduced. The cosine distance between two samples in SPPD space can be computed by Eq.(10). To analyze the attribution of $d_c(y_i, y_j)$,

we firstly analyze the attributions of $y_i^T y_j$ and $|y_i|$.

$$d_c(y_i, y_j) = 1 - y_i^T y_j / (|y_i| |y_j|) \quad (10)$$

Proposition 1: $y_i^T y_j$ decreases with the increase of $d_E(x_i, x_j)$.

Prove: According to Eq.(7) and (8), $y_i^T y_j$ can be rewritten as:

$$\begin{aligned} y_i^T y_j &= \sum_{s=1}^n y_{is} * y_{js} \\ &= \sum_{s=1}^n \exp(-d_E^2(x_i, x_s) / \sigma_i \sigma_s) * \exp(-d_E^2(x_j, x_s) / \sigma_j \sigma_s) \quad (11) \\ &= \sum_{s=1}^n e^{(-d_E^2(x_i, x_s) / \sigma_i \sigma_j) * (\sigma_j / \sigma_s)} * e^{(-d_E^2(x_j, x_s) / \sigma_i \sigma_j) * (\sigma_i / \sigma_s)} \end{aligned}$$

If the samples are uniformly distributed in the feature space, $\sigma_i, \sigma_s, \sigma_j$ are equal, and then $\sigma_i / \sigma_s = 1$ and $\sigma_j / \sigma_s = 1$, as a result, $y_i^T y_j$ can be seen as the joint probability distribution function of two Gaussian distributions that are only with different means. Obviously, the smaller the absolute of subtraction of the means of two Gaussian distributions, the bigger the $y_i^T y_j$, which means that $y_i^T y_j$ decreases with the increase of $d_E(x_i, x_j)$.

If the samples are not uniformly distributed in feature space, $y_i^T y_j$ can be seen as the joint probability distribution function of two Gaussian distributions weighted by σ_i / σ_s and σ_j / σ_s . Furthermore, for the given x_i, x_j and $X = [x_1, x_2, \dots, x_n] \in \mathbb{R}^{m \times n}$, σ_i / σ_s and σ_j / σ_s are two positive constants. As a result, $y_i^T y_j$ also decreases with the increase of $d_E(x_i, x_j)$.

Fig.2 $d_s(x_i, x_s)$ and its derivative, where x - axis is w_{ij}

Proposition 2: $|y_1| \approx |y_2| \approx \dots \approx |y_n|$, when we set suitable values for $\sigma_i, i = 1, 2, \dots, n$.

Prove: According to Eq.(7) and (8), $|y_i|$ can be rewritten as eq.(12). The function curve of $d_s(x_i, x_s)$ is presented in Fig.2. It can be seen from Fig.2 that $d_s(x_i, x_s)$ owns three attributions shown in Eq.(13). Obviously, if we can make that the number of $d_s(x_i, x_s)$ of $y_1, y_2, \dots, y_n$ in each interval are nearly the same, $|y_1| \approx |y_2| \approx \dots \approx |y_n|$.

$$|y_i| = \sqrt{\sum_{s=1}^n y_{is}^* y_{is}} = \sqrt{\sum_{s=1}^n d_s(x_i, x_s)^2} \quad (12)$$

$$\begin{cases} d_s(x_i, x_s) \text{ is large, when } w_{is} \leq 0.3 \\ d_s(x_i, x_s) \text{ decreases quickly, when } 0.3 < w_{is} < 1.2 \\ d_s(x_i, x_s) \text{ is small when } w_{is} \geq 1.2 \end{cases} \quad (13)$$

Now we turn to make the number of $d_s(x_i, x_s)$ of $y_1, y_2, \dots, y_n$ in each interval nearly the same. For the training samples, because the goal of most dimensional reduction methods is maximizing the Euclidean distances across classes and minimizing the Euclidean distances within the class, the Euclidean distances within the class are often much smaller than the Euclidean distances across classes, and then if setting $k = 2 * n_c$ in computing σ_i , $d_e(x_i, x_i^{n_c})$ would be much smaller than $d_e(x_i, x_i^k) / 2$, where n_c is the number of training points in c -th class. As a result, w_{is} has three attributions shown in Eq.(14), which means that the number of $d_s(x_i, x_s)$ of $y_1, y_2, \dots, y_n$ in each interval are nearly the same.

$$\begin{cases} w_{is} \leq 0.3, \text{ when } x_s \in N^{k/2}(x_i) \\ 0.3 < w_{is} < 1.0, \text{ when } x_s \notin N^{k/2}(x_i) \text{ and } x_s \in N^k(x_i) \\ w_{is} \geq 1.0, \text{ when } x_s \notin N^k(x_i) \end{cases} \quad (14)$$

It can be seen from proposition 1 and proposition 2 that $d_c(y_i, y_j)$ nearly increase with $d_e(x_i, x_j)$, which means that the cosine distances in SPPD space increase with the Euclidean distances in low dimension space, and then the gap between dimensional reduction and SRC can be reduced by SPPDAFT.

C. The algorithm of Adaptive Feature Transformation for Classification with Sparse Representation (SPPDSRC)

SPPDAFT is performed before SRC and after dimensional reduction, and the algorithm of SPPDAFT for classification with sparse representation (SPPDSRC) can be concluded as follow:

Algorithm 1 SPPDSRC

Input: labeled samples $\{z_1, z_2, \dots, z_n\} \in \mathbb{R}^h$, the labels of labeled data $\{l_1, l_2, \dots, l_n\}$, a testing sample z , the mapping matrix W obtained by a dimensional reduction method.

Output: the label l of z .

Algorithm:

//Initialization

1: set $k = 2 * n_c$, where n_c is the number of training samples in c -th class.

//Dimensional Reduction:

2: Map $\{z_1, z_2, \dots, z_n, z\} \in \mathbb{R}^h$ to $\{x_1, x_2, \dots, x_n, x\} \in \mathbb{R}^m$ by W , where m is the dimension of features in low dimensional space.

//SPPDAFT:

3: Transform $\{x_1, x_2, \dots, x_n\} \in \mathbb{R}^m \rightarrow \{y_1, y_2, \dots, y_n\} \in \mathbb{R}^n$ by Eq.(7), and transform $x \in \mathbb{R}^m \rightarrow y \in \mathbb{R}^n$ by Eq. (8).

//Traditional Sparse Representation Classification:

4: Set $D = [y_1, y_2, \dots, y_n]$ and set the testing point $x = y$.

5: Compute a by optimizing Eq. (1).

6: Compute E^k for each class by Eq. (2), and get label l of x by Eq.(3)

D. Compared with related algorithms

Although both SPPDSRC and KSRC [6, 7] transform the features to a new feature space before classification, SPPDSRC is different with KSRC. In KSRC, the parameters of kernel functions such as RBF kernel and polynomial kernel are constants, however, the densities of samples are often different, so that found a good kernel parameter for all samples is very hard or impossible. However, in SPPDSRC, the parameters σ_i and σ_j of SPPDAFT are changed with the densities of x_i and x_j , so that SPPDSRC is more adapted to the variability of data. Furthermore, in KSRC, the samples are normalized to have unit l_2 -norm, and then some discriminative information extracted by dimensional reduction could be disrupted. However, in SPPDSRC, the samples need not be normalized to have unit l_2 -norm. Obviously, SPPDSRC can utilize more discriminative information extracted by dimensional reduction.

Although both SPPDSRC and dictionary learning methods such as LCKSVD [9] and FDDL [13] can exploit the discriminative information hidden in the training samples, SPPDSRC is different with these dictionary learning methods. Firstly, in LCKSVD and FDDL, some constraints are added on the sparse coefficients to learn the discriminative information; however, to learn the discriminative information for the sparse coefficients may be not really good for SRC. For example, given $D = [D_1, D_2, \dots, D_C]$ and each D_i has 9 bases, because the constraint of sparse coefficients, each sample could be well represented by only 3 bases, and then two samples in the same class may have much different sparse coefficients. However, in SPPDSRC, we directly make the dictionary containing discriminative information, which is a better way to learn the dictionary for SRC. Secondly, because the constraint of sparse coefficients, the coefficients would be greatly influenced by an unlabeled sample, and then the constraints added on coefficients are also changed sharply, as a result, the unlabeled samples are hardly be used in LCKSVD and FDDL. However, in SPPDSRC, the discriminative information is extracted by a dimensional reduction method, and then the unlabeled samples can be easily used in

SPPDSRC. Thirdly, LCKSVD and FDDL use an iterative approach to learn the dictionary, so that the computational complexity of dictionary learning methods such as LCKSVD and FDDL are much higher than that of SPPDSRC.

IV. Experiments

In this section, several benchmarks of face databases are used to verify the effectiveness of the proposed SPPDSRC, such as: AR database [47], ORL database [48], Yale database [49], and CMU Multi-PIE database [50]. Following algorithms are used to compare: (1) the algorithms that employ dimensional reduction under the SRC framework, including SRC with LRGPSDD [44], DSNPE [30], and LDA [45]. (2) The algorithms that employ LRGPSDD under the KSRC framework, where three kernels are unitized such as: linear kernel, polynomial kernel, and RBF kernel. (3) The algorithms employ dictionary learning under the SRC framework, including LCKSVD [9], DLLR [12], and FDDL [13]. The SPAMS package or GPSR [34] can be used to solve Eq.(1), and the results of them are nearly the same, in this paper, we use SPAMS package to solve Eq.(1), where ε is set to 10^{-4} . All samples for SRC are normalized with length 1, because SRC gets a better result when the samples are normalized with length 1. The parameter of polynomial kernel is set to 3. The parameter of RBF kernel is set by the median value of $1/(\|x_i - \bar{x}\|^2)$, $i = 1, \dots, n$, $\bar{x}$ is the mean of all training samples. The dimension of subspace of LRGPSDD is 10 to 140, where the interval is 20.

For all databases, 2~6 samples per subject are randomly chose for labeled training samples, and 3 samples per subject are randomly chose for unlabeled training samples, while the other samples were used as query samples. The experiments were repeated 30 times to calculate the average recognition rate and the corresponding standard deviation. The accuracy is utilized to evaluate the experiments.

A. Face recognition

AR database [47]. The AR database consists of over 4,000 frontal images from 126 individuals. For each individual, 26 pictures were taken in two separate sessions. In our experiments, a subset that contains 50 males and 50 females with 6 illumination and 8 expression variations in two sessions is used. All images are resized to 32×32 . The accuracies of

competing methods are listed in Table 1 and the accuracies of SRC and SPPDSRC with LRGPSDD, DSNPE, and LDA are listed in Fig.3.

Fig.3 Experiments on AR with different number of training samples.

From the experiments on AR database, we can get four concludes. (1) It can be seen from Fig.3 that most of accuracies of SPPDSRC with dimensional reduction methods are higher than the accuracies of SRC with dimensional reduction, it proves that reducing the gap between dimensional reduction and SRC by SPPDAFT is very important. (2) It can be seen from Table 1 that the accuracies of LRGPSDD+SPPDSRC are higher than the accuracies of LRGPSDD+KSRC, and the accuracies of LRGPSDD+KSRC are higher than the accuracies of LRGPSDD+SRC, it proves that SPPDSRC is better than KSRC and KSRC is better than SRC on ORL. (3) It can be seen from Table 1 that most of accuracies of LDA+SPPDSRC are higher than the accuracies of DLLR, FDDL, and LCKSVD; it proves that the reconstruction ability of each basis should be changed reasonably in learning dictionary. (4) It can be seen from Table 1 that the accuracies of LRGPSDD+SPPDSRC are much higher than the accuracies of FDDL and LCKSVD; it proves that the unlabeled samples are very important for sparse representation classification; however, the unlabeled samples are hardly used in dictionary learning methods such as FDDL and LCKSVD.

TABLE 1
Experiments by using all compared algorithms on AR with different number of training samples.

No. of training Samples	2	3	4	5	6
LRGPSDD+SPPDSRC	76.66 ± 2.40	89.03 ± 1.37	93.57 ± 0.97	95.33 ± 0.90	96.54 ± 0.84
LDA+SPPDSRC	71.47 ± 1.66	85.12 ± 1.35	88.35 ± 1.19	93.83 ± 0.84	95.74 ± 0.95
DSNPE+SPPDSRC	72.31 ± 1.79	84.42 ± 1.25	88.61 ± 1.27	91.73 ± 1.09	94.62 ± 1.13
LRGPSDD+SRC	67.80 ± 3.10	84.43 ± 1.84	89.35 ± 1.59	93.60 ± 1.04	95.38 ± 1.10
LDA+SRC	68.02 ± 1.98	79.19 ± 1.56	85.09 ± 1.34	91.37 ± 1.20	94.20 ± 1.26
DSNPE+SRC	69.36 ± 2.11	82.53 ± 1.63	87.21 ± 1.55	92.85 ± 1.17	94.20 ± 1.30
LRGPSDD+KSRC(Linear)	70.05 ± 2.30	86.67 ± 1.41	91.32 ± 1.08	94.35 ± 1.09	95.60 ± 0.87
LRGPSDD+KSRC(Polynomial)	74.04 ± 4.15	88.38 ± 1.19	92.19 ± 1.33	94.02 ± 0.62	96.21 ± 1.34
LRGPSDD+KSRC(RBF)	74.89 ± 2.13	88.44 ± 1.16	92.63 ± 0.98	94.46 ± 0.63	96.31 ± 0.94
DLLR [12, 2014]	73.40 ± 3.70	78.39 ± 1.83	85.20 ± 1.35	90.78 ± 1.07	92.65 ± 1.15
FDDL [13, 2011]	67.80 ± 1.54	73.09 ± 1.90	87.46 ± 1.60	92.66 ± 1.31	94.07 ± 1.42

LCKSVD[9, 2013]	74.00±1.58	81.69±0.88	86.26±1.37	91.67±0.80	93.32±0.93
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TABLE 2

Experiments by using all compared algorithms on ORL with different number of training samples.

No. of training Samples	2	3	4	5	6
LRGPSSDR+SPPDSRC	86.82±2.56	93.31±2.59	96.38±2.03	97.81±1.56	98.63±1.32
LDA+SPPDSRC	80.95±2.97	87.90±1.84	91.83±2.22	94.25±3.02	94.00±3.18
DSNPE+SPPDSRC	83.73±2.66	89.62±2.03	93.22±2.35	95.72±2.89	96.33±2.45
LRGPSSDR+SRC	84.45±2.38	91.38±2.67	95.58±2.13	97.18±2.29	98.25±1.54
LDA+SRC	79.15±3.22	86.31±2.95	90.00±2.51	93.00±3.13	93.65±3.49
DSNPE+SRC	81.25±2.58	88.53±2.29	92.73±2.17	94.66±2.79	95.72±2.58
LRGPSSDR+KSRC(Linear)	81.70±2.84	90.50±2.45	95.08±1.18	96.88±1.79	97.75±1.97
LRGPSSDR+KSRC(Polynomial)	77.95±5.49	86.44±5.71	91.17±3.73	96.88±2.14	95.00±2.64
LRGPSSDR+KSRC(RBF)	85.35±2.98	91.93±1.86	95.62±1.19	96.88±1.69	98.25±1.54
DLLR [12, 2014]	73.40±3.70	86.26±2.74	89.76±2.12	91.36±3.23	92.08±2.97
FDDL [13, 2011]	76.48±3.24	82.28±3.35	91.33±2.74	93.36±2.66	94.53±2.35
LCKSVD[9, 2013]	81.90±2.62	88.25±2.99	91.50±2.22	92.87±1.89	93.75±1.76

TABLE 3

Experiments by using all compared algorithms on Yale with different number of training samples.

No. of training Samples	2	3	4	5	6
LRGPSSDR+ SPPDSRC	60.67±4.88	73.53±4.90	79.50±4.50	84.00±4.81	84.50±4.87
LDA+ SPPDSRC	61.00±6.68	71.13±4.18	78.58±4.37	79.78±4.61	82.33±6.84
DSNPE+ SPPDSRC	62.53±6.68	71.93±5.62	77.50±5.11	80.55±5.21	83.67±6.18
LRGPSSDR+SRC	55.78±4.49	65.53±5.33	72.42±5.76	77.11±4.97	79.83±5.75
LDA+SRC	56.11±4.80	66.93±4.53	72.67±5.68	74.67±6.01	78.83±6.60
DSNPE+SRC	58.89±4.75	68.33±5.17	73.67±4.96	75.44±5.97	79.22±4.40
LRGPSSDR+KSRC(Linear)	53.44±6.22	64.53±3.74	71.67±5.82	75.89±5.97	79.00±4.49
LRGPSSDR+KSRC(Polynomial)	46.33±5.34	56.53±5.52	59.67±6.13	82.33±4.47	75.33±6.12
LRGPSSDR+KSRC(RBF)	62.00±5.72	72.33±4.37	78.50±5.22	81.78±6.60	84.67±3.31
DLLR [12,2014]	58.78±5.19	67.60±4.57	75.58±4.37	78.66±4.86	79.54±4.03
FDDL [13,2011]	52.56±4.74	64.80±5.61	77.26±4.70	81.69±5.21	81.67±6.08
LCKSVD[9, 2013]	62.06±5.82	69.33±5.22	76.17±5.39	79.86±3.89	80.61±4.29

ORL database [48]. The ORL database consists of 400 frontal images from 40 individuals, all images are resized to 32×32 . The accuracies of competing methods are listed in Table 2 and the accuracies of SRC and SPPDSRC with LRGPSDR, DSNPE, and LDA are listed in Fig.4.

Fig.4 Experiments on the ORL with different number of training samples.

From the experiments on ORL database, we can get four similar concludes. (1) It can be seen from Fig.4 that most of accuracies of SPPDSRC with dimensional reduction are also higher than the accuracies of SRC with dimensional reduction, it proves that reducing the gap between SRC and dimensional

reduction by SPPDAFT is also very important on ORL. (2) It can be seen from Table 2 that the accuracies of LRGPSDR+SPPDSRC are also higher than the accuracies of LRGPSDR+KSRC obviously, SPPDSRC is also better than KSRC on ORL. (3) It can be seen from Table 2 that most of accuracies of LDA+SPPDSRC are also higher than the accuracies of DLLR, FDDL, and LCKSVD; it proves that adding constraints for the sparse coefficients cannot learn good discriminative information for dictionary on ORL. (4) It can be seen from Table 2 that the accuracies of LRGPSDR+SPPDSRC are also much higher than the accuracies of DLLR and LCKSVD.

Fig.5 Experiments on the Yale with different number of training samples.

Yale database [49]. The Yale database consists of 165 frontal images from 15 individuals, and all images are resized to 32×32 . The accuracies of competing methods are listed in Table 3 and the accuracies of SRC and SPPDSRC with LRGPSDR, DSNPE, and LDA are listed in Fig.5. It can be seen from Table.3 and Fig.5 that four similar concludes are also existed on Yale. However, the accuracies of DSNPE+SPPDSRC are higher than the accuracies of LRGPSDR+SPPDSRC when the number of labeled training sample is set to 2; we think the reason is that the assumed manifold in LRGPSDR may be not suitable for this database.

CMU Multi-PIE database[50]. The PIE database contains 41368 images of 68 individuals, each person under 13 different poses, 43 different illumination conditions, and with 4 different expressions. In this paper, we only use five near frontal poses and all the images under different illuminations and expressions, all images are resized to 32×32 . The accuracies of competing methods are listed in Table 4 and the accuracies of SRC and SPPDSRC with LRGPSDR, DSNPE,

and LDA are listed in Fig.6. It can be seen from Table.4 and Fig.6 that four similar concludes are also existed on PIE.

Fig.6 Experiments on PIE with different number of training samples.

TABLE 4
Experiments by using all compared algorithms on PIE with different number of training samples.

No. of training Samples	2	3	4	5	6
LRGPSDR+SPPDSRC	55.47 ± 2.77	70.91 ± 3.47	78.82 ± 2.85	82.84 ± 3.09	85.15 ± 2.85
LDA+ SPPDSRC	48.75 ± 2.88	62.51 ± 3.71	69.78 ± 2.90	72.97 ± 3.14	75.86 ± 2.71
DSNPE+SPPDSRC	50.47 ± 3.26	65.49 ± 3.44	73.18 ± 3.12	75.92 ± 2.90	77.06 ± 3.00
LRGPSDR+SRC	54.56 ± 2.99	68.01 ± 3.21	75.69 ± 3.11	79.46 ± 2.80	82.67 ± 2.96
LDA+SRC	45.12 ± 3.11	59.88 ± 3.86	65.86 ± 2.94	68.80 ± 3.81	71.35 ± 2.35
DSNPE+SRC	47.57 ± 3.23	62.71 ± 3.75	68.77 ± 2.52	71.25 ± 2.40	72.70 ± 2.01
LRGPSDR+KSRC(Linear)	51.55 ± 4.51	67.53 ± 3.32	74.75 ± 3.13	78.67 ± 2.74	81.57 ± 2.98
LRGPSDR+KSRC(Polynomial)	47.92 ± 3.49	60.52 ± 4.46	64.56 ± 3.19	67.65 ± 5.15	66.72 ± 6.14
LRGPSDR+KSRC(RBF)	55.13 ± 4.76	69.50 ± 3.66	77.84 ± 2.24	81.55 ± 2.03	84.11 ± 2.95
DLLR [12,2014]	47.40 ± 3.67	66.18 ± 3.52	69.68 ± 2.67	71.17 ± 3.01	74.38 ± 3.40
FDDL [13,2011]	48.48 ± 2.82	65.49 ± 3.08	71.75 ± 2.71	75.21 ± 2.84	79.52 ± 3.13
LCKSVD [9, 2013]	47.38 ± 3.07	57.16 ± 3.21	68.39 ± 3.56	74.68 ± 2.84	78.85 ± 2.84

TABLE 5
Averaged training time of experiments that with different number of training samples on AR(s)

No. of training Samples	2	3	4	5	6
LRGPSDR	0.2538	0.4358	0.5047	0.5549	0.7913
LDA	0.0335	0.0605	0.0757	0.0882	0.1011
DSNPE	0.1625	0.4123	0.6639	1.004	1.520
DLLR	2.864	3.724	5.430	11.53	20.46
FDDL	146.5	382.4	834.3	1682	2337
LCKSVD	9.975	13.26	20.16	34.06	46.71

B. Computational time

In this subsection, we present the averaged training time of all algorithms, the runtime estimates reported in this paper are obtained on an Intel Core i5-3470 PC with four 3.2GHz processors and 8GB RAM. Obviously, the running time will be greatly increased if these algorithms are performed on an embedded system which is the operating environment of most face recognition system.

In training processing, for LRGPSDR+SPPDSRC, LDA+SPPDSRC, DSNPE+ SPPDSRC, LRGPSDR+SRC, LDA+SRC, DSNPE+SRC, LRGPSDR+KSRC(Linear), RGPSSDR+KSRC(Polynomial), LRGPSDR+ KSRC(RBF), only the training processing of the corresponding dimensional reduction algorithm need to be performed; for FDDL, DLLR,

and LCKSVD, dictionary learning need to be performed. The averaged training time on AR with different number of training samples are presented in Table.5, the averaged training time on other databases have the similar laws. It can be seen from the Table.5 that the averaged training time of FDDL DLLR, LCKSVD are significantly longer than that of LRGPSDR, LDA, and DSNPE; especially, the training time of FDDL is 2337 seconds when 6 labeled training samples per subject are used in training. However, the training time of most face recognition system cannot be too long, for the reason that we may frequently add a person to or remove a person from the face recognition system, which makes that the training processing may be frequently performed. As a result, our algorithm is more important than dictionary learning methods when the face recognition system runs in an

embedded system or the face recognition system is used to recognize a large number of persons.

V. Conclusion

In this paper, an adaptive feature transformation named SPPDAFT is proposed; SPPDAFT transforms features to a new feature space, and makes that the cosine distances among samples in new feature space increase with the Euclidean distances among samples in original space. As a result, the dictionary in new feature space contains the discriminative information extracted by dimensional reduction methods, and then the gap between dimensional reduction and SRC can be reduced. The experiments on four face databases prove that our method is greatly improved SRC, and better than the KSRC and some dictionary learning methods such as FDDL, DLLR, LCKSVD.

Besides the cosine distance among bases and a testing sample influence the reconstruction ability of these bases to this testing sample, the positional relationships among bases and this testing sample are also influence the reconstruction ability of these bases to this testing sample, for example, in LARs algorithm, if the bases are symmetry with each other and the symmetry axis is this testing sample, these bases would have good reconstruction ability to this testing sample, so that in the future we would design a new adaptive feature transformation that considers this case.

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