Single-sample Face Recognition Based on LPP Feature Transfer

JIE PAN, XUE-SONG WANG, AND YU-HU CHENG (Member, IEEE)

1School of Information and Electrical Engineering, China University of Mining and Technology, 221116, Xuzhou, Jiangsu, China

Corresponding author: X.-S. WANG (wangxuesongcumt@163.com)

This work was supported by the National Natural Science Foundation of China under Grant 61472424, by the Fundamental Research Funds for the Central Universities 2014YC07, by the Natural Science Foundation of Jiangsu Province BK20150203.

ABSTRACT Due to its wide applications in practice, face recognition has been an active research topic. With the availability of adequate training samples, many machine learning methods could yield high face recognition accuracy. However, under the circumstance of inadequate training samples, especially the extreme case of having only a single training sample, face recognition becomes challenging. How to deal with conflicting concerns of the small sample size and high dimensionality in one-sample face recognition is critical for its achievable recognition accuracy and feasibility in practice. Being different from conventional methods for global face recognition based on generalization ability promotion and local face recognition depending on image segmentation, a single-sample face recognition algorithm based on Locality Preserving Projection (LPP) feature transfer is proposed here. First, transfer sources are screened to obtain the selective sample source using the whitened cosine similarity metric. Secondly, we project the vectors of source faces and target faces into feature sub-space by LPP respectively, and calculate the feature transfer matrix to approximate the mapping relationship on source faces and target faces in subspace. Then, the feature transfer matrix is used on training samples to transfer the original macro characteristics to target macro characteristics. Finally, the nearest neighbor classifier is used for face recognition. Our results based on popular databases FERET, ORL and Yale demonstrate the superiority of the proposed LPP feature transfer based one-sample face recognition algorithm when compared with popular single-sample face recognition algorithms such as (PC)²A and Block FLDA.

INDEX TERMS Feature extraction, transfer learning, one-sample, face recognition, locality preserving projection.

I. INTRODUCTION

Face recognition has wide applications in areas such as smart card design [1], access control [2], information security [3], law enforcement follow-up [4] and expression cloning [5]. However, in practice it often faces the challenge of having inadequate training samples, especially the extreme case where only one training sample is available for each class of faces and the testing samples often show different appearance from training samples due to factors such as facial expression, illumination and pose angle. Such a challenge limits the current applicability of the face recognition technology in certain applications. It is extremely hard for a conventional transfer learning method to deal with this challenge. Therefore, feature extraction proves to be the key step for achieving high accuracy in single-sample face recognition. In the current literature of single-sample face recognition, there are two main categories of methods: global face recognition and local face recognition.

The first class of global face recognition algorithm is centered on all kinds of improved PCA algorithms, to improve the generalization ability of single sample features. The (PC)²A algorithm proposed by Wu, et al. [6] generates a new mapping of the original image, by compressing and composing the horizontal and vertical dimensions. Similarly, 2DPCA face recognition algorithm [7] has advantages in small-sample recognition due to its higher estimation accuracy of the covariance matrix. Based on 2DPCA, Luo, et al. [8] made further improvements: using 2D discrete cosine transform to extract relevant discrete features. Luh [9] introduced the idea of immunity evolution into PCA, took the source image feature space as the antigen space, updated the immunity network classifier and calculated the affinity coefficient between samples and the classifier. To address the noise problem, Lee [10] estimated the noise parameters by establishing a noise model of face images for the purpose of reducing the impact of noise on images. In addition, using different subspace methods [11-13] can also improve the generalization ability of training samples.

The second class of global face recognition algorithms increases the size of training set by generating virtual samples. To contain more sample information and enhance its adaptability, ROCA [14] combines oriented component analysis based on feature representation difference formed between different sub-spaces. E(PC)²A [15] is an enhanced (PC)²A algorithm, which takes the first-order projection, second-order projection and combined projection as independent samples, respectively, for the increased training set.
In general, the following five measures are mainly adopted to generate virtual samples: 1) addition of random noise [16-17]; 2) mean filtering and the wavelet transform [16]; 3) reconstruction based on the source image of the contourlet transform [18]; 4) kernel principal component analysis and generalized discrimination analysis [19]; 5) multi-angle feature generation of Gabor filtering [20]. In addition to the foregoing methods using the conventional nearest classifier, [16] uses MLP (Multilayer Perceptron), RBF (Radial Base Function) and SVM (Support Vector Machine) to be associated with the proposed virtual sample technique, while [20] allocates one low-accuracy base classifier for each virtual sample and employs EMV (Enhanced Majority Voting) for the final decision making. Recently, Schroff et al. [21] presented a faceNet network, an attempt to seek an embedding function and map images for a compressed Euclidean space, with triplet loss controlled by convolutional neural network (CNN). Eigenvectors obtained in this way can reduce differences of the same face image due to angle, illumination and other conditions as far as possible, while distance between a pair of face images is extended.

When compared with global algorithms, local face recognition algorithms are more suitable for the single-sample problem, since local features can supply more local training samples. A spatial feature based method is proposed to generate the face representation model DCP by detecting the contour curve and angular points [22]. In addition to the geometric representation, Gabor wavelet [23-25] can also efficiently describe the local features of face images. With different models and evaluation mechanisms, such as neural network [26], Hidden Markov Model [27], linear discrimination analysis [28], hybrid local feature [29], local binary model [30] and fractal feature [31], various local segmentation algorithms can be employed. In recent years, Sun et al. [32] considered high-level feature learning through deep network, i.e., deep hidden identity feature (DeepID), which has very high efficiency in multi-class face recognition tasks. Apart from stronger generalization ability with the increase of class, DeepID on the top of CNN requires only a small number of neurons to obtain compressed identity-related features. Compared with global face recognition algorithms, the local algorithms with enlarged sample size are especially more robust under varying facial expression. The main disadvantage is that segmenting face images could result in global information loss and thus its recognition performance degrades under large changes of facial features.

Different from the above conventional algorithms, this paper proposed a single-sample face recognition framework based on locality preserving projection (LPP) feature transfer. As an emerging machine learning method, transfer learning [33] extracts and transfers informative knowledge from the source data to the new target domain. It has been widely applied in areas such as text classification [34], associated information clustering [35] and data regression [36]. Since transfer learning relaxes the restriction on co-distribution of the source task and the target task, it can better reuse the associated data in face recognition. Therefore, we incorporate the transfer learning concept into single-sample face recognition. More specifically, the proposed framework consists of the following main steps: Firstly, we use the whitened cosine similarity to quantify the association between source samples and testing samples, and then acquire a selective sample set; secondly, through LPP, we extract features for the training and testing set to obtain the feature transfer matrix; thirdly, the transfer matrix is applied in the target training sample for transferring to testing features; finally, we employ the nearest neighbor classifier for face recognition. Although the algorithm proposed herein seems a global face recognition algorithm, it is obviously different from the aforementioned conventional global algorithms which focus on enhancing the generalization ability: The feature transfer does not promote the generalization ability of samples, however their macro characteristics can be transferred to be consistent with the testing macro characteristics. This method, to a great extent, will overcome the problem that the intra-class distance is larger than the inter-class distance in the feature space. Though the transfer source cannot be used directly as training samples for learning, exploring related knowledge in the transfer source is still able to assist better learning of training samples in the target domain. Later in this paper, the FERET Database is used to examine the transfer rate and similarity promotion of the proposed algorithm. By testing on different databases such as FERET, ORL and Yale, we also compare the proposed method with different algorithms in terms of recognition accuracy, including PCA [37], LDA [43], LPP [44], and typical single-sample face recognition algorithms such as (PC)\textsuperscript{A} [6], Block FLDA[28], EPS-SEE[50] and DMMMA[51]. The results demonstrate the superiority of the proposed algorithm.

The overall structure of this paper is arranged as follows: in Section II, we briefly review transfer learning and locality preserving projection (LPP) in feature extraction of face recognition. Section III presents the proposed single-sample face recognition framework based on LPP feature transfer. In Section IV, we describe the major components of the proposed framework, including transfer source selection, feature transfer and face recognition. In Section V, we compare the proposed algorithm with different popular single-sample face recognition algorithms. Finally, Section 6 shows the conclusion.

II. RELATED WORK
A. ONE-SHOT LEARNING AND UNSUPERVISED ADAPTATION
The one-shot learning usually faces two challenges: 1) how to extract the discriminative features; 2) how to train the model by the single sample. Li [52] adopts Bayesian probability model to solve the problem. Due to few target task samples, the relevant knowledge in source task is used as the target prior to construct the probability density function of the model parameters. In terms of the continuous motion images, Mahbub [53] adopts space-time descriptor to trace the motion and gestures of the images, form space depth image and extract the features by 2D FFT. Finally, the image gestures are recognized according to relevant coefficients.
In [54], the detection of optical flow is adopted to find the high-level sub-action primitives. It provides a meaningful visualized representation, which can endow the text with labels. Each primitive motion stands for a sub-action element, and is described through 4D mixed Gaussian distribution. In order to extract more meaningful features, 3d-EMoSIFT algorithm is proposed in [55], which is very sensitive to the slight motion changes, and can effectively filter the influence of the static points and slight motion points. A special sparse coding method, SOMP (simulation orthogonal matching pursuit), is used to organize the features to achieve lower reconstruction error and better recognition performance.

While solving the problems of one-shot learning, Romani [56] adopts the optimized binary neurons to recognize the familiarity of once-seen stimuli, and finally gains the optimal constraint between the potential probability and restrain probability. In [57], Bakhtashmotlagh makes use of invariant projection to extract the public information distributed in different domains, that is, to seek the potential low dimension optimal space to minimize the difference distributed in the target for unsupervised domain adaptation.

B. FEATURE TRANSFER LEARNING

Feature transfer learning belongs to the category of inductive transfer learning [33]. For the given source domain $D_s$, the source task $T_s$, the target domain $D_t$ and the target task $T_t$, feature transfer learning aims to find a common LD feature representation of the associated tasks $T_s$ and $T_t$, which can reduce the difference between $T_s$ and $T_t$. Argyriou [38] proposed a way for sharing LD features by solving the following optimization problem:

$$\begin{align*}
\text{arg min} & \sum_{r \in \{s, t\}} \sum_{i=1}^{n} L(y_i, (a_i, U^T x_i)) + \gamma \|A\|_F^2 \\
\text{s.t.} & U \in O^d
\end{align*}
$$

(1)

where $\gamma > 0$ is the regularization parameter, $S$ and $T$ represent the source domain and the target domain, respectively, $A = \{a_i, a_r\} \in \mathbb{R}^{d \times 2}$ is the parameter matrix, $U$ is the orthogonal matrix with size $d \times d$, $n \in \{n_s, n_t\}$ indicates the sample sizes of the source task and target task, and $\{(x_i, y_i)\}$ represent sample data. It maps the original HD data to the LD feature representation, and the $(r, p)$-norm of $A$ is defined as $\|A\|_{r, p} = (\sum_{i=1}^{d} |a_i|^p)^{1/p}$. Through the optimization of Eq. (1), we can obtain the LD representations $U^T X_r$, $U^T X_s$ and relevant parameters in $A$. Furthermore, for being more computationally efficient, this optimization can be transferred to an equivalent convex optimization problem. In [39], Argyriou proposed a spectrum regularization formwork for multi-task structure learning. Lee, et al. [40] proposed a convex optimization algorithm for learning the prior element and feature weights in the relevant task set simultaneously. The prior element can be transferred between the source task and the target task. For the transfer between multitasks, Jebra [41] selected features for better learning of SVM. Ruckert, et al. [42] designed a kernel-based method for inductive transfer learning, with the intention to find the kernel function from the source domain, suitable for the target task.

C. LD FEATURE REPRESENTATION OF A FACE IMAGE

For face recognition, popular methods for LD feature representation include Eigenface, Fisherface and Laplacianface. Eigenface is essentially the Principal Component Analysis (PCA), which was first introduced into the face recognition area in [37], for extracting the principal components of original images, reducing dimensions and computational complexity. For a given original sample set $\{x_1, \ldots, x_n\}$, Eigenface looks for the orthogonal linear mapping matrix $W_{PCA}$ with:

$$x_k^* = W_{PCA}^T x_k$$

(2)

where $x_k \in \mathbb{R}^n$ is the $k$-th original image, $x_k^* \in \mathbb{R}^m$ is its corresponding LD feature expression with $m \ll n$. The optimal $W_{PCA}$ is obtained by maximizing the determinant of the LD feature divergence:

$$W_{PCA} = \arg \max_w \|W^T S_r W\|$$

(3)

where $S_r$ is the total divergence matrix of the sample set.

By solving Eq. (3), we can see that $W_{PCA} = [w_1, w_2, \ldots, w_m]$ contains the eigen vectors of the original sample set divergence matrix $S_r$ corresponding to the $m$ largest eigen values. Since Eigenface cannot distinguish within-class divergence and between-class divergence in the calculation of sample set divergence, the optimal mapping matrix obtained not only maximizes the between-class divergence, but also maximizes the within-class divergence. Fisherface separates the two kinds of divergence, and obtains the optimal mapping matrix as follows:

$$W_{LDA} = \arg \max_w \frac{\|W^T S_r W\|}{\|W^T S_w W\|}$$

(4)

where $W_{LDA}$ represents the general eigen-vectors of the between-class divergence $S_r$ and the within-class divergence $S_w$ corresponding to $m$ largest eigen-values. Due to the high dimensionality (HD) of facial features, Belhumeur [43] first lowered the feature dimensionality to the order of $S_w$ using PCA, and then calculate the feature mapping matrix.

Locality Preserving Projection [44] is a linear approximate of non-linear Laplacian mapping, which can transfer the samples from the original space to a new space and ensure that the neighborhood of samples remains unchanged: i.e., near samples in the original space will remain near in the new feature space. The optimal Locality Preserving Projection matrix can be obtained as:
\[
W_{LPP} = \arg \min \sum_i z^T X L X^T z
\]

\[s.t. \quad z^T D X D^T z = 1\]

where \(D\) is a diagonal matrix with diagonal elements as \(D_{ij} = \sum_k w_{jk}\). \(L = D - W\) is a Laplacian matrix, \(X\) is the data matrix.

In addition to the aforementioned PCA, LDA, LPP and other methods, Bartlett [45] also proposed using independent component analysis for describing LD features of face images. This method intends to look for a group of independent bases in the sample space. Furthermore, Fisherface was also developed. Enhanced fisher discrimination analysis model [46], robust discrimination analysis model [47] and other related methods were further proposed successively for better face recognition.

**III. PROPOSED METHOD**

**A. SYSTEM PRINCIPLE DIAGRAM**

The system principle diagram of the proposed single-sample face recognition framework based on LPP feature transfer is as shown in Figure 1. In the middle of the figure, \(I_m^w\) means the single target training sample and \(q_m\) represents its associated macro facial appearance characteristic. In the right upper corner, \(I_n^w\) means the target testing sample, with its associated macro facial appearance characteristic \(q_n\). Our goal is to recognize the face \(I_n^w\) by means of the face \(I_m^w\). Generally, there is a major difference between \(q_m\) and \(q_n\). Therefore it may cause considerable errors if we directly use 1-NN classifier [48] to classify the face \(I_n^w\). To solve the problem, this paper proposed a LPP feature transfer algorithm, which can make full use of abundant related source samples to assist target task. The proposed method can be summarized as follows: Given the single training sample \(I_m^w\) with macro characteristics \(q_m\), use the transfer source \(TS = \{I_1, I_2, ..., I_L\}\) and the associated source macro characteristic set \(Q_S = \{q_1, q_2, ..., q_k\}\) to assist \(I_m^w\) in recognizing the testing sample \(I_n^w\) with the macro characteristic \(q_n\) \((q_m \neq q_n)\).

To achieve this recognition purpose, the proposed framework consists of three major stages: I. Transfer Source Selection, II. Feature Transfer Learning, and III. Target Face Recognition. More specifically, we first filter the transfer source \(TS\) to obtain the auxiliary samples with the same or similar macro characteristics as \(q_m\) and \(q_n\). These two groups of samples are called selective transfer sources \(SS_m\) and \(SS_n\). Then we extract features from \(SS_m\) and \(SS_n\) respectively, and calculate the feature transfer matrix between \(q_m\) and \(q_n\) to assist the training sample \(I_m^w\) to actualize \(I_m^w \rightarrow I_n^w\): i.e., transferring its training macro characteristic \(q_m\) to the testing macro characteristic \(q_n\). Finally the 1-NN classifier is employed to recognize the testing sample \(I_n^w\) under the condition of the same macro characteristic \(q_n\).

**B. TRANSFER SOURCE SELECTION**

The major task of this stage is to get the selected samples with the same macro characteristic of the target training sample and the testing sample for the purpose of further feature transfer. The stage is shown in Figure 2, and can be mainly divided into three steps: 1) to select the source images with the macro characteristic of the training sample; 2) to replace the true testing sample with the testing macro characteristic source image; and 3) to select the source images of the macro characteristic of the testing sample.

In the first step of selecting, we obtain the samples with the
Whitened cosine similarity can be used to resolve the problem with pattern recognition based on biological feature matching, which can properly reflect the association between different pattern vectors. Its expression is:

$$\delta_{WC}(U, V) = \frac{(W^TU)^T(W^TV)}{\|W^TU\| \|W^TV\|}$$  \hspace{1cm} (6)$$

where $U$ and $V$ are different pattern vectors, $W$ is the whitened operator and $\| \|$ means the norm operator. In solving $W$, WCS only takes into account the global information of samples, while the calculation of the covariance matrix $\Sigma$ is based on the overall distribution: i.e., $\Sigma = E[(x-M_o)(x-M_o)^T]$, $M_o = E(x)$ is the overall mean vector, assuming different classes have the same sample distribution and thus ignoring the differences between different classes; under the circumstance that such an assumption is violated, the similarity measure could be biased. A specific within-class whitened cosine (WWC) similarity measure in combination with the prior probability is used in this paper. Unlike WCS, WWC not only considers the distribution differences of different classes, but also considers the effect of different prior probabilities.

Source sample covariance matrix $\Sigma_w$ can be written as follows in space $R^d$ in combination with face recognition:

$$\Sigma_w = \sum_{i=1}^{k} P(I_i) \sum_{j=1}^{k} (I_i^d - AF_i)(I_j^d - AF_j)^T$$  \hspace{1cm} (7)$$

where $AF_i = \sum_{j=1}^{k} I_j^d$ is the mean face of Class $i$ , $P(I_i)$ means the corresponding prior probability, with $P(I_i) = \text{num}(I_i)/\text{num}(TS)$ , and $\text{num}(\cdot)$ is the number of samples. The comparison of similarity is usually carried out within the LD feature sub-space $R^d (d << D)$, so $\Sigma_w$ is PCA decomposed as $\Sigma_w = \Phi_w \Lambda_w \Phi_w^T$, to obtain the pairwise orthogonal feature vector matrix $\Phi_w$ and the feature value diagonal matrix $\Lambda_w$. To avoid any unbalanced variance distribution upon mapping the source feature to $R^d$, $I_i^d (i = 1, 2, ..., L)$ and $I_f^d$ must be whitened, with the whitening operator as:

$$W_w = \Phi_w \Lambda_w^{-1/2}$$  \hspace{1cm} (8)$$

In fact, setting $I_f^d = W_w^T I_i^d$, we have the $R^d$ sub-space within-class sample covariance as:

$$\Sigma_w' = \sum_{i=1}^{k} P(I_i) \sum_{j=1}^{k} (I_i^d - AF_i)(I_j^d - AF_j)^T$$

$$= \sum_{i=1}^{k} P(I_i) (\Phi_w \Lambda_w^{-1/2})^T$$

$$= \sum_{i=1}^{k} (I_i^d - AF_i)(I_i^d - AF_i)^T (\Phi_w \Lambda_w^{-1/2})$$

$$= \Lambda_w^{-1/2} (\Phi_w \Sigma_w \Phi_w^T) \Lambda_w^{-1/2} = \Lambda_w^{-1/2} \Sigma_w \Lambda_w^{-1/2} = E_d$$

where $AF_i = \sum_{j=1}^{k} I_j^d / \text{num}(I_i)$ is the Class- $i$ mean face within the sub-space $R^d$ and $E_d$ is the Order- $d$ unit matrix. Obviously, the $W_w$ operator causes the $I_f^d$ features $f_1, f_2, ..., f_d$ upon dimension-reduction to be pairwise orthogonal, with equal independent variance of their own: i.e.,
assuming equal contributions of \( f_1, f_2, \ldots, f_d \) on classifier learning, without ignoring the effect of any \( f_l \) \((l = 1, 2, \ldots, d)\) on the learning result. Accordingly, the cosine similarity within the \( \mathbb{R}^d \) space is:

\[
\delta_{\text{wce}}(I^o_i, I^p_T) = \frac{(W^T_i I^o_i)^T(W^T_i I^p_T)}\|W^T_i I^o_i\| \|W^T_i I^p_T\| \tag{10}
\]

We set \( \theta_1 \) as the similarity threshold value, and take the samples \( I^o_i \) \((i = 1, 2, \ldots, L; q_i = q_m)\) which satisfy \( \delta_{\text{wce}} \geq \theta_1 \) into the transfer source selective sample set \( SS \), i.e., \( SS = \{I^o_i, I^p_T\} | \delta_{\text{wce}}(I^o_i, I^p_T) \geq \theta_1 \} \), where \( I^o_i \) is the relevant sample of \( I^p_T \) under the testing macro characteristics \( q_m \).

### C. FEATURE TRANSFER AND FACE RECOGNITION

**Algorithm 1 Single-sample Face Recognition Algorithm Based on LPP Feature Transfer**

**Objective:** Recognize face image \( I^o_i \).

**Inputs:** training sample set \( T \) : a total of \( N \) classes, one sample in each class; transfer source \( TS \) : a total of \( K \) classes \((T \cap TS = \emptyset)\), \( s \) samples in each class.

1) **Initialization:** Set the similarity threshold \( \theta_1 \), locality preserving threshold \( \theta_2 \), sub-space dimensions \( d \) and prior probability \( P_1, P_2, \ldots, P_L \).

2) **Transfer source selection**
   a) Calculate the average face \( \bar{AF}_i \) in each class \( i \) of \( TS \).
   b) Obtain the within-class sample covariance matrix \( \Sigma_i \) according to Eq. (7).
   c) Solve the whitened operator \( W_n \) in Eq. (8), take it into Eq. (10) and calculate similarity \( \delta_{\text{wce}}(I^o_i, I^p_T) \) between the source sample \( I^o_i \) and the target training sample \( I^p_T \).
   d) Select source samples \( I^o_i \) satisfying \( \delta_{\text{wce}} \geq \theta_1 \) as the selective transfer source \( SS \).

3) **Feature transfer based on LPP**
   a) Generate graph \( G \) by \( SS \), and calculate degree diagonal matrix \( D \), graph Laplacian matrix \( L \).
   b) Solve the feature transfer matrix \( A \) in Eq. (12), with the corresponding feature value \( \lambda_0 < \lambda_1 < \cdots < \lambda_{d-1} \), \( A = [a_0, a_1, \ldots, a_{d-1}] \), and the feature projection within the sub-space \( \mathbb{R}^d \) is \( I^o_i = A^T I^o_i \), \( I^p_T = A^T I^p_T \). The target of feature transfer is to look for the mapping relation \( h \), which satisfies:

\[
I^o_i = h_{x_n \rightarrow x_n} (I^o_i) (i = 1, 2, \ldots, N) \tag{13}
\]

where \( N = 0.5 \text{num}(SS) \) indicates the number of sample pairs \( (I^o_i, I^p_T) \) in \( SS \). With the feature transfer matrix \( H \) used to approximate \( h_{x_n \rightarrow x_n} \), the transfer error is:

\[
\mathcal{E} = \frac{1}{N} \sum_{i=1}^{N} \| I^o_i - I^p_T H_{x_n \rightarrow x_n} \| \tag{14}
\]

The ideal \( H_{x_n \rightarrow x_n} \) should make \( \mathcal{E} \rightarrow 0 \). In practice, due to the transfer error for \( N \) samples, the optimal \( H_{x_n \rightarrow x_n} \) is to minimize \( \mathcal{E} \), i.e.:

\[
H_{x_n \rightarrow x_n} = \arg \min \mathcal{E}(H_{x_n \rightarrow x_n}) \tag{15}
\]

Then \( h_{x_n \rightarrow x_n} (I^o_i) = I^p_T H_{x_n \rightarrow x_n} (i = 1, 2, \ldots, N) \) is consolidated into a formula as:

\[
\begin{bmatrix}
(I^o_1)^T \\
(I^o_2)^T \\
\vdots \\
(I^o_N)^T
\end{bmatrix} \times \begin{bmatrix}
H_{x_n \rightarrow x_n}
\end{bmatrix}_{d \times d} = \begin{bmatrix}
(I^p_1)^T \\
(I^p_2)^T \\
\vdots \\
(I^p_N)^T
\end{bmatrix}_{d \times d} \tag{16}
\]
Mark $\tilde{I}_N = [I_{x_1}^e, I_{x_2}^e, ..., I_{x_N}^e]^T$, $\tilde{I}_N = [I_{y_1}^e, I_{y_2}^e, ..., I_{y_N}^e]^T$. Eq. (16) can be simplified as $\tilde{I}_N^e = \tilde{H}_{e_x \rightarrow e_y} = I_{y_i}^e$. And $\tilde{I}_N$ and $\tilde{I}_N^e$ are both $N \times d$ order matrix, thus:

$$\tilde{H}_{e_x \rightarrow e_y} = (\tilde{I}_N^e)^{-1} \tilde{I}_N$$

(17)

where $(\tilde{I}_N^e)^{-1}$ is Moore-Penrose inverse matrix of $\tilde{I}_N^e$. After obtaining the feature transfer matrix $H_{e_x \rightarrow e_y}$, feature transfer sample $I_x^e$ is made available as $I_x^e = I_x^e \cdot H_{e_x \rightarrow e_y}$.

Given the training sample $I_x^e$, the testing sample $I_y^e$ and the transfer sources with each class of samples $I_i$ containing $K$ macro characteristics, to evaluate the effect of feature transfer, we define the transfer rate $TE$ as follows:

$$TE = \frac{CS(I_x^e, I_y^e) - CS(I_x^e, I_i^e)}{CS(I_x^e, I_i^e)}$$

(18)

When $TE > 0$, $CS(I_x^e, I_y^e) > CS(I_x^e, I_i^e)$, indicating the feature transfer is a positive transfer; i.e., upon being transferred, the similarity between the training sample and testing sample is higher; otherwise, it is a negative transfer. Here $CS(\cdot)$ indicates the between-sample cosine similarity, with the formula as follows:

$$CS(X, Y) = \frac{(X)^T Y}{\|X\| \|Y\|}$$

(19)

After feature transfer, the training sample can be ensured to have the same or similar macro characteristics with the testing sample, and the conventional distribution of small-sample face images is changed and the new sample distribution can better satisfy the assumption that the between-class distance is greater than the within-class distance. In this case, 1-NN can be used to obtain good classification results.

IV. EXPERIMENTAL RESULTS
A. FACE FEATURE TRANSFER AND SIMILARITY ANALYSIS

<table>
<thead>
<tr>
<th>TABLE 1. Macro characteristics descriptions of the FERET-b face database.</th>
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<td>facial expression</td>
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<td>angle</td>
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</table>

To demonstrate the effectiveness of the proposed algorithm, the popular FERET face database is investigated. FERET includes, in total, 13,539 face images of different races, genders, ages, expressions, illumination and angles, in 1,565 classes respectively. In this paper, we use FERET-b, the b series of FERET, as experimental database. FERET-b includes 200 classes of faces and each has seven macro characteristics $q_i: ba, q_i: bb, q_i: bc, q_i: bf, q_i: bg, q_i: bj$ and $q_i: bk$, as described in Table 1. As for deflection angle, “+” indicates right deflection and “-” indicates left deflection. Additionally, each image is preprocessed to have the face area with size $80 \times 80$.

In order to verify the effectiveness of selecting transfer source, two groups of experiments are performed as shown in Figure 3, Table 2 and Table 3. In Table 2, the first row and the first column ‘ba-bk’ denote the macro characteristics of face images showed in the first and second rows of Figure 3(a). Similar relationship exists between Table 3 and Figure 3(b). The data in both Tables are the within-class whitened cosine similarity of related samples. It can be seen that, human faces with the same macro characteristics are more similar.

<table>
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<tr>
<th>TABLE 2. WWC of different transfer source images.</th>
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<td>bk</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE 3. WWC of different transfer source images.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ba</td>
</tr>
<tr>
<td>ba</td>
</tr>
<tr>
<td>bb</td>
</tr>
<tr>
<td>bc</td>
</tr>
<tr>
<td>bf</td>
</tr>
<tr>
<td>bg</td>
</tr>
<tr>
<td>bj</td>
</tr>
<tr>
<td>bk</td>
</tr>
</tbody>
</table>

From FERET-b, the first 100 classes of people are taken as the transfer source and among the rest 100 classes of people, 4 classes are selected randomly as the training and testing samples. Sub-space dimension of feature transfer is $d = 200$ and similarity threshold is $\theta_l = 0.6$. Figure 4 illustrates the face transfer effect when using LPP features, where each group of macro characteristics $ba$ is the given training feature, $bb$·$bk$ is
the transfer feature. From the figure, it is noted that since the feature transfer carries on the mapping relation \( h_{n \rightarrow x_k} \) \((k = 2, 3, ..., 7)\) between different projection features in the transfer source, even though having different color, gender and facial features, 4 groups of faces can all be transferred and generalized into a series of feature transferred images with different poses, illumination and expressions, according to the training feature ba.

Table 4 reports the statistical results corresponding to Figure 4, where TF, OF and TE mean transfer feature, original feature and transfer efficiency respectively. No.1-4 represents 4 groups of experiments corresponding to Figure 4. Data under TF is similarity degree \( CS_{df}(I_f, I_{t_k}) \) between TF and the testing feature, while data under OF is similarity degree \( CS_{df}(I_f, I_{t_k}) \) between OF and testing feature. In the table, the last line Avg. corresponds to the mean value of each indicator. From Table 4, it can be observed that before and after transfer, the similarity within feature sub-space is remarkably promoted; according to transfer efficiency, each group of experiment is observed with an average promotion of 70.4%-164.5%. Actually, face data has the obvious features different from the general machine learning data: i.e., the discreteness of feature distribution causes the within-class sample distance with different macro feature to be often greater than the between-class sample distance with the same features. Feature transfer makes within-class samples have the same features, thus being nearer and having higher similarity.

Due to such targeted feature transfer, in the experiment on 4 groups with different colors, genders and ages 6 types of macro characteristics transfer, the lowest positive transfer efficiency can be still 14.0%, thus constraining the incidence of negative transfer to a great extent. Additionally, the transfer efficiency differs for different features, but the transfer efficiency of features bj and bk is the valley value of each experiment group. By comparing with Figure 4, it may be understood that bj and bk correspond to expression and illumination feature, respectively. On one hand, the expression of face has higher specificity and the feature mapping relation in the transfer source can hardly be matched perfectly with target feature transfer; on the other hand, due to the transfer of illumination feature, the target training image and testing image have the same or approximate illumination intensity, but affect the facial and other features of face image inevitably. Due to these two factors, the transfer of features bj and bk is more difficult than other features.

**TABLE 4. Cosine similarity and transfer efficiency measures between associated features (LPP).**

<table>
<thead>
<tr>
<th>F.</th>
<th>No.1</th>
<th>No.2</th>
<th>No.3</th>
<th>No.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>TF</td>
<td>OF</td>
<td>TE</td>
<td>TF</td>
<td>OF</td>
</tr>
<tr>
<td>bb</td>
<td>0.5301</td>
<td>0.2589</td>
<td>104.8%</td>
<td>0.7496</td>
</tr>
<tr>
<td>bc</td>
<td>0.4611</td>
<td>0.1466</td>
<td>214.6%</td>
<td>0.7081</td>
</tr>
<tr>
<td>bf</td>
<td>0.5722</td>
<td>0.1781</td>
<td>221.3%</td>
<td>0.5765</td>
</tr>
<tr>
<td>bg</td>
<td>0.5913</td>
<td>0.2985</td>
<td>98.1%</td>
<td>0.7043</td>
</tr>
<tr>
<td>bj</td>
<td>0.3734</td>
<td>0.2384</td>
<td>56.6%</td>
<td>0.6674</td>
</tr>
<tr>
<td>bk</td>
<td>0.7375</td>
<td>0.1447</td>
<td>77.8%</td>
<td>0.5546</td>
</tr>
<tr>
<td>Avg</td>
<td>0.5443</td>
<td>0.2559</td>
<td>128.9%</td>
<td>0.6601</td>
</tr>
</tbody>
</table>

**FIGURE 4.** Feature transferred face images from 4 different classes.

**FIGURE 5.** Effect comparisons of different feature transfer algorithms (a) Original features OFs (b) FT-PCA transfer features (c) FT-LDA transfer features (d) FT-LPP transfer features (e) Actual features TFs.
To verify the rationality and effectiveness of LPP in face feature transfer, a comparison of transfer effect is conducted between FT-LPP using Laplacian face transfer, the feature face transfer FT-PCA using PCA, and the Fisher face transfer FT-LDA using LDA feature extraction. Figure 5 presents the 6 groups of experimental results, where (a) are original features OFs, (b) are FT-PCA transfer features, (c) are FT-LDA transfer features, (d) are FT-LPP transfer features, and (e) are target real features TFs. Generally face recognition is performed within the feature sub-space. To illustrate the visual feature transfer effect, the transfer feature within the sub-space is further projected back and reduced to the original sample space \( R^0 \). From Figure 5, it is observed that the transfer effect of the FT-LDA algorithm attaching importance to discrimination of within-class divergence \( S_W \) and between-class divergence \( S_B \) and FT-LPP emphasizing on local feature structure is obviously superior to FT-PCA. Actually, as the classic linear dimension-reduction feature extraction method, PCA attaches more importance to the global structure of sample features, requiring for maximizing variance for samples within the feature sub-space; i.e., feature extraction matrix \( W_{PCA} = \arg \max_{W} \sum_{i=1}^{N} (I_i^t - \mu)^2 = \arg \max_{W} \sum_{i=1}^{N} (W I_i^t - AF_i)^2 \), due to the essence of emphasizing the global feature presentation, it lacks of objectiveness in the process of feature extraction and transfer.

Although the macro features of testing samples can be transferred, the original facial features and other local information are lost to some extent. Comparatively, FT-LPP transferred, the original facial features and other local extraction and transfer. Presentation, it lacks of objectiveness in the process of feature extraction matrix \( W_{LPP} = \arg \max_{W} (W S_W W^T) / (W S_W W^T) \) makes the different types of features within the sub-space have a higher divergence on the one hand and lower between-class divergence on the other hand; due to higher feature class identification, macro characteristics transfer becomes more rational than FT-PCA. Being different from FT-PCA and FT-LDA of global feature transfer, in feature projection, FT-LPP, a local structure feature transfer algorithm based on spectrum theory requires \( W_{LPP} = \arg \min_{W} \sum_{i=1}^{N} (I_i^t - \mu)^2 w_j = \arg \min_{W} \sum_{i=1}^{N} (W I_i^t - W \mu)^2 w_j \). Obviously, due to the reward and punishment effect of connection weight \( w_j \), the sub-space features \( I_i^t \) and \( I_j^t \) will keep the same relation with the original samples \( I_i \) and \( I_j \); i.e., able to, in the process of feature extraction and transfer, preserve the association information between different macro characteristics of original samples and ensure the precision of feature transfer.

Table 5 further presents the results in terms of cosine similarity \( CS \) and transfer efficiency \( TE \). In the Table, OF, FT-PCA, FT-LDA and FT-LPP represent 4 classes of algorithms respectively, i.e., no transfer, PCA-based feature transfer, LDA-based feature transfer and LPP-based feature transfer. Six sets of experiments are conducted and the average result is shown in the last row. From Table 5, it can be noted that the similarity results between the three transferred feature images with the target feature are consistently higher than that of the corresponding original feature images. Consequently, all algorithms can achieve positive transfer, i.e., \( TE > 0 \). As for FT-LDA and FT-LPP, though Figure 5 cannot directly draw a conclusion on which of the two algorithms is better, due to the local feature preserving property of Laplacian face, the sub-space facial features after feature transfer is closer to the original training image and FT-LPP can achieve a higher similarity with the target image, e.g., with the average transfer efficiency of 151.9% in FT-LPP, higher than the 128.4% of FT-LDA.

### C. SINGLE-SAMPLE RECOGNITION ACCURACY RESULTS

<table>
<thead>
<tr>
<th>No.</th>
<th>OF</th>
<th>FT-PCA</th>
<th>FT-LDA</th>
<th>FT-LPP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.3032 /</td>
<td>0.3556 17.3%</td>
<td>0.3782 24.7%</td>
<td>0.5336 76.0%</td>
</tr>
<tr>
<td>2</td>
<td>0.2372 /</td>
<td>0.4482 89.0%</td>
<td>0.5024 111.8%</td>
<td>0.5692 140.0%</td>
</tr>
<tr>
<td>3</td>
<td>0.1882 /</td>
<td>0.2823 50.0%</td>
<td>0.4509 139.6%</td>
<td>0.3754 99.4%</td>
</tr>
<tr>
<td>4</td>
<td>0.4828 /</td>
<td>0.4974 3.0%</td>
<td>0.5220 8.1%</td>
<td>0.6267 29.8%</td>
</tr>
<tr>
<td>5</td>
<td>0.1687 /</td>
<td>0.1970 16.8%</td>
<td>0.6640 293.5%</td>
<td>0.8636 411.8%</td>
</tr>
<tr>
<td>6</td>
<td>0.2707 /</td>
<td>0.4492 65.9%</td>
<td>0.7913 192.3%</td>
<td>0.6892 154.6%</td>
</tr>
<tr>
<td>Avg.</td>
<td>0.2751 /</td>
<td>0.3716 40.3%</td>
<td>0.5315 128.4%</td>
<td>0.6096 151.9%</td>
</tr>
</tbody>
</table>

Table 6 Recognition accuracy comparisons between different single-sample face recognition methods

<table>
<thead>
<tr>
<th>Method</th>
<th>FERET-b</th>
<th>ORL</th>
<th>Yale</th>
<th>Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA[37]</td>
<td>18%</td>
<td>20%</td>
<td>35%</td>
<td>15%</td>
</tr>
<tr>
<td>LDA[43]</td>
<td>20%</td>
<td>19%</td>
<td>31%</td>
<td>27%</td>
</tr>
<tr>
<td>LPP[44]</td>
<td>25%</td>
<td>22%</td>
<td>37%</td>
<td>31%</td>
</tr>
<tr>
<td>(PC)²[A][6]</td>
<td>45%</td>
<td>44%</td>
<td>33%</td>
<td>37%</td>
</tr>
<tr>
<td>Block FLDA[28]</td>
<td>59%</td>
<td>58%</td>
<td>70%</td>
<td>53%</td>
</tr>
<tr>
<td>EPS-SEE[50]</td>
<td>72%</td>
<td>73%</td>
<td>69%</td>
<td>75%</td>
</tr>
<tr>
<td>DMMA[51]</td>
<td>80%</td>
<td>85%</td>
<td>79%</td>
<td>81%</td>
</tr>
<tr>
<td>FT-PCA</td>
<td>65%</td>
<td>67%</td>
<td>47%</td>
<td>61%</td>
</tr>
<tr>
<td>FT-LDA</td>
<td>81%</td>
<td>79%</td>
<td>64%</td>
<td>76%</td>
</tr>
<tr>
<td>FT-LPP</td>
<td>89%</td>
<td>85%</td>
<td>71%</td>
<td>80%</td>
</tr>
</tbody>
</table>

To examine the recognition accuracy of the proposed algorithm for single-sample face recognition, FT-PCA, FT-LDA and FT-LPP are experimentally compared with their corresponding versions without feature transfer (i.e., the PCA [37], LDA [43] and LPP [44] methods) and classical single-sample face recognition algorithms (PC)²[A] [6], Block FLDA [28], EPS-SEE [50] and DMMA [51]. Table 6 reports the experimental results of different algorithms on data sets FERET-b, ORL and Yale. The setting rules for data sets FERET-b, ORL and Yale are as follows: 1) FERET-b: select 100 classes as the transfer source, select 1 training sample for each class from the remaining 100
classes, randomly select 1 testing sample each time for 100 times; 2) ORL: select 20 classes of samples as the transfer source, select 1 training sample for each class from the remaining 20 classes, select 1 testing sample at random, and repeat the process 50 times; 3) Yale: select 10 classes of samples as the transfer source, select 1 training sample for each class from the remaining 5 classes, select 1 testing sample at random, and repeat the process 50 times.

To guarantee the fairness of parameter setting, parameters are set for (PC)^2 A and Block FLDA with reference to [6] and [28] respectively. (PC)^2 A has the projection weight $\alpha = 0.25$ and the eligibility race contribution $\theta = 0.9$ ; Block FLDA segments the sub-pattern area as 5x5, with the neighbor number $k_n = 3$. From Table 6, it can be observed that the recognition performances of algorithms based on feature transfer such as FT-PCA, FT-LDA and FT-LPP are higher than that of PCA, LDA, LPP, (PC)^2 A, and Block FLDA, which do not include feature transfer. PCA, LDA and LPP are classical face recognition algorithms, whose recognition performances generally increase when the number of training samples increases; For the extreme case of the number of training samples, i.e., when $n = 1$, their recognition performances are the poorest. Actually, PCA, LDA and LPP essentially conduct feature extraction and dimension-reduction of original samples from different perspectives, to reduce computational cost, enhance the generalization ability and improve the recognition accuracy.

![FIGURE 6. ROC curve of different single-sample face recognition methods in FERET-b.](image_url)

However when there is only one training sample and it has different macro characteristics from the testing sample, for such classical methods, the more accurate the feature extraction, the more difference in macro characteristics will be preserved between the training sample and the testing sample. Therefore these classical algorithms generally don’t perform well in single-sample face recognition. Comparatively, before PCA is used, (PC)^2 A conducts, in advance, the composition of different dimension projections to ensure that the combined projection can have lighter computational cost and better generalization ability in the circumstance that the mean intensity of images remains unchanged, thus improving the recognition accuracy without increasing the size of training samples. Compared with the EPS-SEE and DMMA algorithm, the proposed algorithm is superior to these two algorithms in terms of recognition accuracy under the most feature transfer. Figure 6 provides ROC curves of single-sample face recognition methods mentioned above, where the data in the figure legend are area under ROC and above viewpoints can be confirmed according to the curve trends.

For the multi-segmentation local face recognition algorithm, Block FLDA increases training samples by segmenting sub-areas as well as has better local discrimination ability for testing samples. This enables it to have a high recognition accuracy for samples with changes in local expression, such as the recognition of the feature bj in FERET-b and the data set Yale focusing on expression changes. As for feature transfer based algorithms FT-PCA, FT-LDA and FT-LPP, Figure. 5 visually illustrates and Table 4 statistically reports the similarity results and transfer efficiency between samples before and after transfer. Obviously, a higher similarity after transfer contributes to a higher face recognition accuracy of the proposed FT-LPP.

V. CONCLUSIONS

A single-sample face recognition algorithm based on LPP feature transfer is proposed in this paper. Several important observations can be summarized as follows: (1) The proposed method can effectively deal with the concerns of small sample size and high dimensionality in single-sample face recognition. The use of transfer source increases intangibly the scale of training sets and allows better estimation of within-class and between-class covariance matrices; (2) Not only inherent features resulting from face posture and expression changes can be transferred, but the environmental features resulting from external factors such as illumination intensity can also be transferred; (3) Different from conventional single-sample face recognition algorithms, feature transfer for a testing sample preserves the global face information as well as takes into account the local feature information of the testing sample; (4) To avoid negative transfer and make feature transfer more efficient, WCS is applied to evaluate the similarity of the target task and transfer sources to form the selective transfer source; (5) The LPP feature extraction method based on face manifold approximation is superior to the conventional PCA and LDA. It maintains local features and captures face sub-spaces by structuring graphs so that the process of feature transfer can be conducted in a low-dimensional space; (6) Compared with Block FLDA, LPC and other methods, the proposed method can efficiently avoid the problem of global feature information damage due to image segmentation and is robust for face angle change; (7) Since the expression features show relatively high differences between different people, its transfer efficiency is the lowest.

REFERENCES


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