Globality-Locality Preserving Projections for Biometric Data Dimensionality Reduction

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Abstract

In a biometric recognition task, the manifold of data is the result of the interactions between the sub-manifold of dynamic factors of subjects and the sub-manifold of static factors of subjects. Therefore, instead of directly constructing the graph Laplacian of samples, we firstly divide each subject data into a static part (subject-invariant part) and a dynamic part (intra-subject variations) and then jointly learn their graph Laplacians to yield a new graph Laplcian. We use this new graph Laplacian to replace the original graph Laplacian of Locality Preserving Projections (LPP) to present a new supervised dimensionality reduction algorithm. We name this algorithm Globality-Locality Preserving Projections (GLPP). Moreover, we also extend GLPP into a 2D version for dimensionality reduction of 2D data. Compared to LPP, the subspace learned by GLPP more precisely preserves the manifold structures of the data and is more robust to the noisy samples. We apply it to face recognition and gait recognition. Extensive results demonstrate the superiority of GLPP in comparison with the state-of-the-art algorithms.

1. Introduction

Dimensionality reduction is a fundamental task in machine learning, biometrics and computer vision. Although it has been studied over decades, it still experiences a vivid enthusiasm nowadays. In many biometric systems, the dimensionality reduction step is an irreplaceable part of the system, since the effective low-level features are often high-dimensional and the unnecessary dimensions need to be pruned [5, 23].

Over past decades, many impressive dimensionality reduction algorithms have been proposed, such as Principal Component Analysis (PCA) [25, 29], Linear Discriminant Analysis (LDA) [2, 16], Nonnegative Matrix Factorization (NMF) [15], Locality Preserving Projections (LPP) [11], locally linear embedding (LLE) [21]. Among them, several manifold-based dimensionality reduction algorithms are more popular in the recent decade [3, 11, 12, 15, 31], since some manifold learning studies show that the high-dimensional samples reside on the nonlinear manifolds e.g. [21]. The greatest merit of such approaches over the traditional dimensionality reduction algorithms, such as LDA and PCA, is that they do not impose any sample distribution assumption and can handle the nonlinear case. Locality Preservation Projection (LPP) is one of the representative manifold-based dimensionality reduction algorithms. LPP constructs an adjacency matrix to weight the distance between each pair of sample points for learning a projection which can preserve the local manifold structures of data. The weight between two nearby points is much greater than that between two distant points. So if two points are close in the original space, then they will be close in the learned subspace as well. LPP has been successfully applied in many domains and many impressive LPP algorithms have been proposed from different aspects in the recent decade, such as Discriminant LPP (DLPP) [31], Orthogonal LPP (OLPP)[4], Parametric Regularized LPP (PRLPP) [17].

The core of LPP algorithms is the construction of graph Laplacian, since the graph Laplacian encodes the manifold structure of the samples. LPP provides a supervised way and an unsupervised way to construct the graph Laplacian. The supervised way puts an edge between each pair of homogenous samples. In this way, the graph Laplacian can only capture the geometric structure of dynamic part (intra-subject variations), such as pose and view, since the static part of a subject, which is a part invariant to the subject, is counteracted during the construction. More specifically, the weight of an edge is often assigned as a kernalization of the distance between the pair of homogenous samples, $||x_i - x_j||_p = ||\Delta x_i - \Delta x_j||_p$, where x_i and x_j are two homogenous samples, $\bar{x}$ is the mean sample of a subject and $\Delta x_i = x_i - \bar{x}$ and $\Delta x_j = x_j - \bar{x}$ are the offsets of x_i and

x_j to the mean sample, $\bar{x}$. In such case, the mean part of subject, $\bar{x}$, which is deemed as a static part and invariant to the subject, will not have an impact on the construction of the graph Laplacian. However, in biometrics, the samples of different subjects are extracted all from the same biometric trait. That means that the subjects should share a lot of properties. So, the static parts of subjects, such as shape and texture, which are invariant to the subject, should also play an important role in the manifold of biometric data. In the contrast, the unsupervised way can consider both the previous two factors via assigning an edge between the each pair of the samples in the same neighborhood. However, the main issue of this way is that the neighborhood relationship may not reveal the real relationship among the samples, since the samples are often very noisy, which can corrupt the manifold if there is no supervision of labels.

In this paper, we assume the manifold of data is the result of the interaction between the manifold of intra-subject factors (dynamic factors) and the manifold of subject-invariant factors (static factors). So, we address the previous issues via jointly learning the graph Laplacians of dynamic factors and static factors. The new graph Laplacian is the concatenation of these two graph Laplacians. We use it to replace the original graph Laplacian in LPP to present a new LPP algorithm. Since the manifold of dynamic factors is among the samples in a subject while the manifold of static factors is among the subjects, we name this new LPP algorithm Globality-Locality Preserving Projections (GLPP). Our work can also be applied to the other LPP algorithms. Moreover, we extend GLPP into a 2D version named 2DGLPP for dimensionality reduction of 2D data. Seven biometric databases are used for validating our work in face recognition and gait recognition. The results of experiments show that GLPP outperforms the state-of-the-art algorithms and achieves a remarkable improvement over LPP.

2. Locality Preserving Projections (LPP)

In this section, we will introduce the basic notations of dimensionality reduction and the LPP algorithm [11], which is the most relevant dimensionality reduction algorithm to our work.

Let $X = [x_1, ..., x_n] \subset \mathcal{R}^m$ be the sample set. LPP aims at learning a projection w that it can translate the original sample space X into a subspace $Y = w^T X = [y_1, ..., y_n] \subset \mathcal{R}^d$, in which the geometric structure of data can be well preserved. Such optimal projection w can be solved by minimizing the summation of the weighted distance between pair of two samples as follows

$$\sum_{i,j} (y_i - y_j)^2 S_{ij} \tag{1}$$

where the weight S_{ij} is the i,jth entry of the adjacency weight matrix S, which measures the closeness of two points x_i and x_j in the original high-dimensional sample space. This results in a heavy penalty to apart two neighboring points far away in a learned subspace. In such way, the learned projection ensures that if samples x_i and x_j are close in the sample space then they are close as well in the learned subspace. To a supervised task, the labels can be incorporated into the objective function

$$\sum_{i,j} (y_i - y_j)^2 S_{ij} = \sum_{c \in C} \sum_{i,j \in c} (y_i - y_j)^2 H_{ij}^c \tag{2}$$

where H_{ij}^c is the entry of the adjacency matrix of the samples belonging to subject c. In such case, matrix S is actually denoted as follows

$$S = \begin{pmatrix} H_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & H_C \end{pmatrix} \tag{3}$$

With regard to the weighting of edges, Dot-product weighting and Heat Kernel Weighting are two commonly adopted weighting schemes [11].

Finally, the objective function of LPP can be reduced to

$$\begin{aligned} &\sum_{i,j} (y_i - y_j)^2 S_{ij} \\ &= 2(\sum_{i,j} w^T x_i D_{ii} x_i^T w - \sum_{i,j} w^T x_i D_{ij} x_j^T w) \\ &= 2(w^T X(D - S) X^T w)) = 2(w^T X L X^T w) \end{aligned} \tag{4}$$

where D is a diagonal matrix and its entries are column (or row, since S is symmetric) sum of S, $D_{ii} = \sum_j S_{ij}$. The matrix $L = D - S$ is exactly the graph Laplacian [7].

Furthermore, a constraint is imposed in LPP for normalization

$$\hat{w} = \arg \min_{w^T X D X^T w = 1} (w^T X L X^T w) \tag{5}$$

Since the matrices XLX^T and XDX^T are all symmetric and positive semi-definite, this problem can be solved by eigenvalue decomposition. The best LPP projection w is the eigenvector corresponding to the minimum nonzero eigenvalue of $(XDX^T)^{-1} XLX^T$.

3. Proposed Algorithm

3.1. Globality-Locality Preserving Projections

We separate the manifold of data into two sub-manifolds of static factors and dynamic factors to precisely capture the manifold structure among the noisy samples. We use the straightforward way to separate the dynamic part and static part of subject that let the mean sample of subject as the static part and the difference between the sample and the mean sample of its corresponding subject be the dynamic part. Certainly, some other advanced technique can be applied to separate these two factors.

Let vector $C = [1, 2, ..., p]$ be the subject labels. Matrix $X_c, c \in C$ is the subset of samples belonging to class c. Matrix $U = [u_1, ..., u_i, ..., u_p] \subset \mathcal{R}^m, i \in C$ denotes the mean space of samples where u_i is the mean sample of the subject i. Matrix $M = [m_1, ..., m_i, ..., m_p] \subset \mathcal{R}^d, i \in C$ denotes the projected mean sample space via projecting the original mean sample space U into the optimal subspace.

In the learned subspace, the manifolds of the static and dynamic factors in the high-dimensional samples should be both preserved. These two tasks can be respectively solved by minimizing the following two objectives

$$\Phi_s = \sum_{i,j \in C} (m_i - m_j)^2 B_{ij} \tag{6}$$

$$\Phi_d = \sum_{c \in C} \sum_{i,j \in c} (\Delta y_i - \Delta y_j)^2 S_{ij} \tag{7}$$

where $\Delta y_i = y_i - m_c, i \in c$ and $\Delta y_j = y_j - m_c, j \in c$. Jointing these two objectives leads to the objective of our model, which can jointly solve the previous two issues

$$\begin{aligned} \Psi &= \Phi_s + \beta \Phi_d \qquad (8) \\ &= \sum_{i,j \in C} (m_i - m_j)^2 B_{ij} + \beta \sum_{c \in C} \sum_{i,j \in c} (\Delta y_i - \Delta y_j)^2 S_{ij} \end{aligned}$$

where β is a positive to control the tradeoff of the preservations of geometric structures of static factors and dynamic factors. Matrices S and B are the adjacency weight matrices of the dynamic factor objective term, Φ_d, and the static factor objective term, Φ_s respectively.

Finally, Equation 8 can be reduced as follows

$$\begin{aligned} \Psi &= \sum_{i,j \in C} (m_i - m_j)^2 B_{ij} + \beta \sum_{c \in C} \sum_{i,j \in c} (\Delta y_i - \Delta y_j)^2 S_{ij} \\ &= \sum_{i,j \in C} (m_i - m_j)^2 B_{ij} + \beta \sum_{c \in C} \sum_{i,j \in c} (y_i - y_j)^2 S_{ij} \\ &= \sum_{i,j \in C} (w^T u_i - w^T u_j)^2 B_{ij} \\ &+ \beta \sum_{c \in C} \sum_{i,j \in c} (w^T x_i - w^T x_j)^2 S_{ij} \\ &= 2(w^T U G U^T w - w^T U F U^T w) \qquad (9) \\ &+ 2\beta \sum_{c \in C} (w^T X_c D_c X_c^T w - w^T X_c S_c X_c^T w) \\ &= 2w^T (U K U^T + \beta \sum_{c \in C} (X_c L_c X_c^T)) w \\ &= w^T A w \end{aligned}$$

where K and $L_c, c \in C$ are the graph Laplacian of the static factors and the graph Laplacian of the dynamic factors in subject c respectively. Since K and L_c are all the positive semi-definite matrices, A is a positive semi-definite matrix. Therefore, this problem reduces to

$$\hat{w} = \arg \min_w (w^T A w) \tag{10}$$

can be solved by the eigenvalue decomposition. Since the conventional supervised LPP algorithm only considers the manifold among the homogenous samples while our method also considers the manifold of static factors of subjects which is in the subject level, we name the proposed LPP algorithm Globality-Locality Preserving Projections (GLPP).

The first d best projections w are corresponding to the first d minimum nonzero eigenvalues of A. Finally, we can obtain the projections $W = [w_1, w_2, ..., w_d]$.

3.2. A 2D Extension of GLPP (2DGLPP)

In biometrics, sometimes, the input features are the matrices, such as images. In this section, we give an extension of GLPP algorithm which supports the dimensionality reduction in such case. The advantage of this extension over GLPP is that it can take original structures of 2D data into consideration.

2DGLPP considers the input data as a matrix instead of a vector. Let us consider a set of samples $G = [g_1, g_2, ..., g_N]$ taken from an $m \times n$ dimensional sample space. For dimensionality reduction, we should design a projection w which maps the original $m \times n$ sample into a m dimensional feature space, $y_i = g_i w, i = 1, 2, ..., N$. In this subspace, the samples should enjoy same properties that in the subspace learned by GLPP.

Same as GLPP, we can get the graph Laplacians of static and dynamic factors of subjects. However, we can not employ these graph Laplacian directly since the input data is a matrix. For catering the requirement, the Laplacian matrices should be transformed as follows

$$T = L \otimes I_m = \begin{pmatrix} l_{11} & l_{12} & \cdots & l_{1n} \\ l_{21} & l_{22} & \cdots & l_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ l_{n1} & l_{n2} & \cdots & l_{nn} \end{pmatrix} \otimes \left(\underbrace{\begin{matrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{matrix}}_{m} \right) \tag{11}$$

where the operator $\otimes$ is the Kronecker product of the matrices. Then, the model of 2DGLPP can be further expressed as follows

$$\begin{aligned} \widetilde{\Psi} &= 2w^T (M (K \otimes I_m) M^T + \beta \sum_{c \in C} (G_c (L_c \otimes I_m) G_c^T)) w \\ &= 2w^T (M Z M^T + \beta \sum_{c \in C} (G_c T_c G_c^T)) w \qquad (12) \end{aligned}$$

where $G_c = [g_1^T, g_2^T, \cdots, g_l^T] \subset G, c \in C$ is a $ml \times n$ matrix generated by arranging all the samples ,belong to subject c, in column. Similarly, $M = [m_1^T, m_2^T, ..., m_c^T], m_i = \sum_{j \in c} g_j$ is a $mc \times n$ matrix generated by arranging mean sample of each subject in column. Finally, this problem is formulated to the standard GLPP problem and can be solved by eigenvalue decomposition.

4. Experiments

In this section, we apply GLPP algorithm in two biometric tasks, face recognition and gait recognition, to validate its effectiveness.

4.1. Datasets and Compared Methods

AR [18], ORL [22], FERET [20], Yale [2], LFW-A [27], Mobo [8] and OU-ISIR-A [24] databases are adopted to evaluate the proposed algorithms. AR, ORL, FERET, Yale, LFW-A databases are the face databases while Mobo and OU-ISIR-A databases are the gait databases. Note, following [19], AR and FERET are the subsets of their original databases. LFW-A is the aligned version of LFW database. Following the settings of [30], we only keep the subjects who have more than 5 samples. Since LFW-A is a very challenging database, we use LBP to represent the images. OU-ISIR-A is a very recent gait database aims to study the cross-speed gait recognition. It has already define the gallery and probe sets. Their numbers are 1424 and 1434. Moreover, we use the Speed Invariant Gait Template (SIGT) [13] as the features of gait data.

Name	Subjects	#Samples	Feature	Dimension
ORL [22]	40	400	Grayscale	1024
Yale [2]	15	165	Grayscale	1024
FERET [20]	72	432	Grayscale	10304
AR [18]	120	1680	Grayscale	2000
LFW-A [27]	274	4758	LBP [1]	2891
Mobo [8]	25	4812	SIGT [13]	33792
OU-ISIR-A [24]	34	1424\1434	SIGT [13]	33792

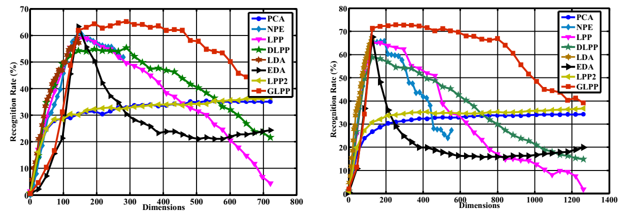
Table 1. The involved databases

Seven state-of-the-art dimensionality reduction algorithms are used to compare with GLPP. They are Principal Component Analysis (PCA) [25], Linear Discriminant Analysis (LDA) [2], Exponential Discriminant Analysis (EDA) [32], Neighborhood preserving embedding (NPE) [10], Supervised Locality Preserving Projections (LPP) [11], Unsupervised Locality Preserving Projections (LPP2) [11] and Discriminant Locality Preserving Projections(DLPP) [31]. Three state-of-the-art dimensionality reduction algorithms for 2D data, namely 2DPCA [29], 2DLDA [16] and 2DLPP [6], are used to compare with 2DGLPP. In the experiments, Nearest Neighbour Classifier (NN) and Linear Regression Classifier (LRC) are used for classification. In all experiments, β is fixed to 10000.

Moreover, three recent regression-based face recognition methods, namely Linear Regression Classification (LRC) [19], Sparse Representation Classification (SRC) [28] and Relaxed Collaborative Representation (RCR) [30], are considered as compared face recognition methods. Three influential gait recognition methods, namely, Gait Energy Image (GEI) [9], Chrono-Gait Image (CGI) [26] and Differential Composition Model (DCM) [14] are adopted for comparison in gait recognition.

4.2. Face Recognition

In Yale, AR, ORL, FERET databases, we apply the standard cross-validation to evaluate the algorithms, since the sample number per subject in these databases are same.



(a) First Subset (b) Second Subset

Figure 1. Dimensions vs Accuracies in LFW-A database.

With regard to the LFW-A database, we follow the experimental settings in [30]. The database has been separated into two subsets. The first subset is constructed by the subjects whose sample numbers range from 6 to 10. The second subset is constructed by the subjects whose sample numbers are above 10. We respectively set the training number per subject in first and second subsets to 5 and 10. All the regression-based face recognition methods are directly applied to the raw samples.

Methods	Recognition Rates ± Standard Deviation, %			
	Yale	FERET	ORL	AR
PCA+NN	88.67±2.8	84.03±1.0	85.25±0.4	66.73±0.1
LDA+NN	95.33±4.7	90.74±3.3	93.00±0.7	58.57±1.5
EDA+NN	97.33±0.0	92.36±3.6	91.50±3.5	60.89±0.6
NPE+NN	96.00±5.7	93.51±1.3	90.00±4.5	61.61±0.2
LPP+NN	96.67±4.1	92.82±2.3	90.75±3.9	61.19±0.3
LPP2+NN	88.00±0.0	86.57±0.7	85.25±1.1	67.80±1.1
DLPP+NN	97.33±3.8	90.51±4.4	93.75±3.1	65.95±2.7
GLPP+NN	**98.67±1.9**	94.44±3.9	**95.75±1.8**	67.44±2.9
PCA+LRC	90.66±5.7	85.18±0.7	90.25±1.8	68.69±0.3
LDA+LRC	96.00±3.8	88.19±5.6	91.75±0.4	59.11±0.9
EDA+LRC	**98.67±1.9**	93.75±3.6	93.50±4.2	63.69±0.8
NPE+LRC	97.33±3.8	92.82±3.6	92.00±3.5	62.32±0.6
LPP+LRC	97.33±3.8	92.82±1.0	93.00±2.8	63.51±1.1
LPP2+LRC	92.67±4.7	88.89±0.7	90.25±1.8	71.01±0.9
DLPP+LRC	96.67±4.2	91.44±2.3	94.50±4.9	68.51±2.8
GLPP+LRC	**98.67±1.9**	**94.67±3.8**	95.25±2.5	**71.30±1.0**
RCR [30]	97.33±3.8	93.52±1.3	93.75±3.9	76.96±1.4
SRC [28]	97.33±2.8	91.44±0.4	92.00±3.5	63.87±0.4
LRC [19]	90.67±5.7	84.72±0.0	88.75±3.2	68.75±0.4

Table 2. Recognition performance comparison (in percents) using Yale, ORL, FERET and AR databases.

Tables 2 and 3 present the recognition results in five face databases. It is very clear that GLPP outperforms all the compared dimensionality reduction algorithms in the experiments of all five databases and outperforms the compared regression-based face recognition methods in all experiments except the one in AR database. Another point we can learn from the results is that GLPP obtains a remarkable improvement over LPP. For example, the gains of GLPP over LPP in subset1 and subset2 of LFW-A database are respectively 5.75% and 13.2%.

Figure 1 shows the relationship between retained dimensions and the recognition accuracies on LFW-A database. The recognition accuracy of GLPP can keep top in almost all dimensions and is more robust to the number of re-

Methods	Recognition Rate (Retained Dimensions)	
	subset1	subset2
PCA+NN	35.34%(529)	34.25%(1261)
LDA+NN	58.90%(141)	67.17%(125)
EDA+NN	63.29%(145)	54.15%(127)
NPE+NN	61.37%(145)	65.83%(191)
LPP+NN	58.90%(145)	65.12%(169)
LPP2+NN	36.71%(721)	36.77%(1261)
DLPP+NN	55.34%(289)	58.84%(127)
GLPP+NN	65.20%(289)	72.86%(253)
PCA+LRC	48.49 %(529)	51.89%(1177)
LDA+LRC	58.08%(141)	63.15%(125)
EDA+LRC	65.47%(697)	69.10%(1135)
NPE+LRC	61.37%(226)	66.21%(476)
LPP+LRC	61.92%(505)	68.17%(1135)
LPP2+LRC	53.69%(457)	63.19%(1177)
DLPP+LRC	59.17%(649)	63.19%(883)
GLPP+LRC	**67.67%(673)**	**81.37%(1009)**
RCR [30]	65.75%	75.17%
LRC [19]	48.49%	51.76%
SRC [28]	63.01%	69.26%

Table 3. Recognition performance comparison (in percents) using LFW-A database

tained dimensions. Table 4 represents the recognition results of several 2D-dimensionality reduction algorithms on Yale database. Same as GLPP, 2DGLPP outperforms the compared algorithms.

Methods	2D linear methods-recognition rate (ARA±STD)			
	2DPCA [29]	2DLDA [16]	2DLPP [6]	2DGLPP
One-out	**99.39±2.0**	95.15±10.4	98.18±3.1	**99.39±2.0**
Five-fold	98.67±1.8	94.67±6.9	98.67±1.8	**99.33±1.5**
Two-fold	96.00±3.8	90.67±5.7	97.33±1.9	**99.39±2.0**

Table 4. Recognition performance comparison (in percents) using Yale database

4.3. Gait Recognition

On Mobo database, there are four subsets, namely Slow, Fast, Ball and Incline. In these experiments, we let the Slow subset be the gallery set while the other three as the probe set. With regard to OU-ISIR-A database, we follow the experimental settings in [13]. It separates the gallery set into three subset according to the walking speed. The speeds of the subjects of subset1, subset2 and subset3 are respectively 2-4 km/h, 5-7 km/h and 8-10 km/h.

Tables 5 and 6 respectively present the rank-1 gait recognition accuracies on these two databases. Same as the results in face recognition, clearly, GLPP outperforms all the compared algorithms. Another interesting phenomenon found in the experiments is that, in the noisy subsets, GLPP can get more gains over LPP. For instance, the gain of GLPP over LPP is 2.5% in Fast subset while the number is 14.2% in Incline subset. This is because the samples in Incline subset are much more noisy than the ones in Fast subset. This phenomenon verifies that our proposed method can better capture geometric structure of data in the noisy samples.

We also draw Cumulative Match Characteristic (CMC) curves on OU-ISIR-A database in Figure 2. The observa-

Gallery \ Probe	Rank-1 Recognition Accuracy		
	Slow\Fast	Slow\Ball	Slow\Incline
PCA+NN	81.88%	30.84%	30.35%
LDA+NN	92.67%	58.91%	32.11%
EDA+NN	92.60%	64.66%	40.61%
NPE+NN	92.32%	59.57%	35.79%
LPP+NN	90.31%	58.91%	35.52%
LPP2+NN	84.37%	31.60%	34.04%
DLPP+NN	90.87%	62.45%	37.19%
GLPP+NN	92.88%	**66.57%**	**49.74%**
PCA+LRC	83.26%	33.91%	33.51%
LDA+LRC	84.02%	41.28%	28.25%
EDA+LRC	93.22%	58.62%	40.52%
NPE+LRC	92.19%	63.22%	42.89%
LPP+LRC	91.42%	58.04%	36.05%
LPP2+LRC	83.96%	31.40%	31.23%
DLPP+LRC	91.45%	61.78%	40.18%
GLPP+LRC	**93.36%**	65.71%	47.81%
GEI [9]	84.85%	67.24%	54.65%
CGI [26]	79.25%	67.33%	52.37%
DCM [14]	92.00%	/	/

Table 5. Recognition performance comparison (in percents) using Mobo database

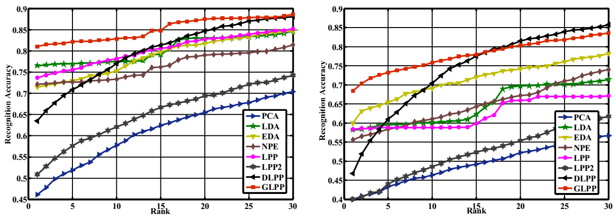
Training Set	Rank-1 Recognition Accuracy		
	subset1	subset2	subset3
PCA+NN	42.63%	46.14%	40.10%
LDA+NN	64.53%	73.59%	53.79%
EDA+NN	61.73%	71.49%	59.97%
NPE+NN	65.10%	72.12%	55.62%
LPP+NN	63.20%	71.77%	56.32%
LPP2+NN	48.03%	50.91%	40.10%
DLPP+NN	63.13%	63.48%	46.77%
GLPP+NN	**70.15%**	**81.04%**	**68.61%**
PCA+LRC	49.30%	50.35%	42.42%
LDA+LRC	59.41%	62.99%	51.26%
EDA+LRC	58.22%	70.08%	57.51%
NPE+LRC	44.31%	45.08%	44.87%
LPP+LRC	57.79%	71.77%	54.07%
LPP2+LRC	50.63%	52.53%	42.28%
DLPP+LRC	63.55%	64.75%	49.51%
GLPP+LRC	69.66%	79.28%	66.64%
GEI [9]	64.75%	69.87%	59.90%
CGI [26]	61.03%	66.15%	45.72%

Table 6. Recognition performance comparison (in percents) using OU-ISIR A database

tions from Figure 2 demonstrate the superiority of GLPP.

5. Conclusion

In a biometric recognition task, we separated the samples of a subject into the dynamic part (intra-subject factors) and the static part (subject-invariant factors). We jointly learn the graph Laplacians of these two parts and concatenate them as a new graph Laplaican to replace the original graph Laplacian in LPP. We name this new algorithm Globality-Locality Preserving Projections (GLPP). Its advantage over supervised LPP is that it take between-subject variations into consideration while the advantage over unsupervised LPP is that it can utilize the supervised information to alleviate the impact of noises of samples to the manifold learn-



(a) Subset2 (b) Subset3

Figure 2. The CMC curves on OU-ISIR-A database.

ing. We apply GLPP to face recognition and gait recognition. The results demonstrate the superiority of GLPP over other state-of-the-art dimensionality reduction algorithms. Our work is a general trick for constructing the noisy robust graph Laplacian. So it can be applied to all LPP algorithms.

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