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Face Recognition Usinig Fuzzy Discriminiant Locality Preserving Projection

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Abstract: A novel approach, namely Fuzzy Discriminant Locality Preserving Projection (FDLPP), is proposed for dimensionality reduction to improve the performance of Discriminant Locality Preserving Projection (DLPP). FDLPP which is based on Maximum Margin Criterion (MMC), pursues to maximize the difference between the locality preserving between-class scatter and locality preserving within-class scatter instead of the ratio. In FDLPP, fuzzy k-nearest is implemented to obtain correct local distribution information and the pursuit of better classification results. Blending the membership degree into the definition of the Laplacian scatter matrix acquire to fuzzy Laplacian scatter matrix. Experiments on ORL, FERET and Yale face databases show the effectiveness with the change in illumination and viewing directions of the proposed method.

Key words: Discriminant locality preserving projection, fuzzy k-nearest, dimensionality reduction, maximum margin criterion, fuzzy laplacian scatter matrix

INTRODUCTION

Dimensionality reduction has been the key technology in many fields of information processing, for instance pattern recognition and data mining. In face recognition, extracting useful identifying information in the training samples which is including a lot of redundant information is necessary before classification. To overcome the difficulty, it is usually to learn a subspace in which we can detect the reduced intrinsic dimension in the high dimensional space. This needs to map the sample points form input space to a low dimensional space by linear or nonlinear transformation. Many useful techniques, two popular linear subspace methods are PCA (Turk and Pentland, 1991) and LDA (Fukunaga, 1990), for dimensionality reduction has been developed over the recent decades.

One limitation of PCA and LDA is that they effectively see only the linear global Euclidean structure but the essential structure of data with nonlinear sub-manifold cannot be explored. A lot of manifold learning-based approaches focus on preserving the local structure, such as Locally Linear Embedding (LLE) (Roweis and Saul, 2000), Laplacian Eigenmaps (LE) (Belkin and Niyogi, 2003) attracted considerable attention over the past years. The embedding function of the linear techniques is defined everywhere in the input space rather than only defined for a set of data samples such as non-linear embedding techniques (Dornaika and Assoum, 2013). This is the main superiority of dimensionality reduction using the linear approaches over the non-linear ones.

Recently, a graph-based method which is based on Locality Preserving Projections (LPP) (He and Niyogi, 2003) technique was proposed for linear dimensionality reduction (LDR) for overcome the out-of-sample problem. As a linear unsupervised technique, LPP preserves the locality structures of data is superior to PCA. Furthermore, extensive experiments shown that it can give better performance than the supervised technique LDA in some cases. Many approaches such as Optimal Locality Preserving Projection (O-LPP) (Chen *et al*., 2011), DLPP/MMC (Lu and Zuo, 2011), Orthogonal Isometric Projection (O-IsoProjection) (Lu *et al*., 2010) and Discriminant Locality Preserving Projections (DLPP) (Yu *et al*., 2006) are proposed based on LPP to advance the classification performance of LPP. DLPP is proposed as an approach of maximizing the average distances of between-class and minimizing the average variances for the same class.

In this study, we improve the discriminant locality preserving projections to overcome the singularity encountered by DLPP and blend the fuzzy technology to increase the worst-case performance for each individual and a Fuzzy Discriminant Locality Preserving Projections (FDLPP) algorithm is proposed. Furthermore, maximum margin criterion (Lu *et al*., 2010) is introduced in FDLPP. By taking advantage of the technology of fuzzy sets, a number of studies have been carried out for fuzzy image filtering, fuzzy image segmentation and fuzzy edge detection with an ultimate objective to cope with the factor of uncertainty being inherently present in many problems of image processing and pattern recognition (Kwak and Pedrycz, 2005). In fact, the FDLPP algorithm

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can achieve better estimation of class means by using the membership degree to describe the distribution of training samples. Experimental results show the effectiveness of the proposed approach.

RELATED WORKS

Given a training set of face images $X = [x_1, x_2, ..., x_N] \in \Re^{n \times N}$, each face image x_i belongs to one of the C face classes $\{X_1, X_2, \ldots, X_C\}$. The objective function of DLPP can be expressed as follows (Chen *et al.*, 2011):

$$A = \arg\max \sum_{i,j=1}^{C} (\bar{m}_i - \bar{m}_j) B_{ij} \Big/ \sum_{c=1}^{C} \sum_{i,j=1}^{n_i} \left(y_i^c - y_j^c\right) W_{ij}^c \quad (1)$$

where, n_i is the number of samples in the ith class, y^c_i represents the ith projected vector in the cth class, m_i and m_j is separately the mean projected vector for the ith class and jth class, W^c_{ij} represents the elements of within-class weight matrix and $W^c_{ij} = \exp(-\|x^c_i - x^c_j\|^2/\delta^2)$, B_{ij} represents the elements of between-class weight matrix and $B_{ij} = \exp(-\|f_i - f_j\|^2/\delta^2)$, where δ is an empirically determined parameter, x^c_i represents the ith vector in the cth class, f_i is the mean of the ith class. Thus, the between-class weight matrix is $B = [B_{ij}]$, the within-class weight matrix is $W = \text{diag}\{W^{(1)}, W^{(2)}, \ldots, W^{(C)}\}$. It is clear that both B and W are symmetric positive semi-definite matrices.

Suppose that the mapping from x_i to y_i is A, then, the objective Eq. 1 can be rewritten as:

$$J(A) = \frac{A^T F H F^T A}{A^T X L X^T A} \quad (2)$$

where, L and H are Laplacian matrices. $L = D - W$, $D = \text{diag}\{D_1, D_2, \ldots, D_C\}$, D_i is a diagonal matrix and its elements are column (or row) sum of $W^{(i)}$; $H = E - B$, E is a diagonal matrix and its elements are column (or row) sum of B. $F = \{f_1, f_2, \ldots, f_C\}$.

PROPOSED FDLPP

The results of the FKNN are used in the computations of the statistical properties of the patterns such as the mean value and scatter covariance matrices, the constructs being at heart of the Fisherface method. Taking into account the membership grades, the mean vector of each class $\tilde{m}_i$ is calculated as follows:

$$\tilde{m}_i = \sum_{j=1}^{N} u_j^c x_j \Big/ \sum_{j=1}^{N} u_j^c \quad (3)$$

According to Eq. 3, the fuzzy between-class weight matrix B_{fuzzy} are redefined as follows:

$$B_{ij}\_\text{fuzzy} = \exp(-\|\tilde{m}_i - \tilde{m}_j\|^2 / \delta^2) \quad (4)$$

A reasonable criterion for choosing a 'good' map is to minimize the following fuzzy within-class scatter under appropriate constraints:

$$\begin{aligned}
&\sum_c \sum_{i,j} (y_i^c - y_j^c) U_j^c W_{ij}^c \\
&= \sum_c \sum_{i,j} (v^T x_i^c - v^T x_j^c) U_j^c W_{ij}^c \\
&= \sum_{ij} v^T x_j U_j W_{ij} x_i^T v - \sum_{ij} v^T x_j U_j W_{ij} x_j^T v^T \\
&= v^T X D_{fuzzy} X^T v - v^T X (U.*W) X^T v^T \\
&= v^T X D_{fuzzy} X^T v - v^T X W_{fuzzy} X^T v^T
\end{aligned}$$

where, the fuzzy within-class weight matrix W_{fuzzy} is defined as follows:

$$W_{ij}^c\_\text{fuzzy} = U_j^c \times \exp(-\|u_i^c x_i^c - u_j^c x_j^c\|^2 / \delta^2) \quad (5)$$

Then the fuzzy Laplacian matrices L_{fuzzy} and H_{fuzzy} are calculate as:

$$L_{fuzzy} = D_{fuzzy} - W_{fuzzy} \quad (6)$$

$$H_{fuzzy} = E_{fuzzy} - B_{fuzzy} \quad (7)$$

where, D_{fuzzy} is a diagonal matrix and its elements are column (or row) sum of W_{fuzzy}, E_{fuzzy} is a diagonal matrix and its elements are column (or row) sum of B_{fuzzy}.

Finally, by combining Eq. 6-7, the objective Eq. 2 can be redefined as:

$$J(A) = \frac{A^T M H_{fuzzy} M^T A}{A^T X L_{fuzzy} X^T A}$$

From the classical Fisher criterion function, we know the larger the ratio of the between-class scatter to the within-class, the easier samples can be separated.

FDLPP requires that matrix XLX^T be nonsingular. For many applications involving the SSS problem this matrix is singular. In fact, as long as the dimension of sample M is greater than the number of samples N, XLX^T must be singular. Thus FDLPP cannot be applied directly. The goal of MMC for feature extraction is to seek k discriminant vectors $a_1, a_2, \ldots, a_k$ such that the trace of locality preserving between-class scatter is maximized and the trace of locality preserving within-class scatter is minimized after training samples are projected on these vectors. According to the idea of MMC (Lu *et al.*, 2010), the objective function of FDLPP is defined as follows:

$$J(A) = tr(A^T(S_b - \alpha S_w)A) \quad (8)$$

where, $S_b = MH_fM^T$, $S_w = aX_LfX^T$.

The parameter α is a nonnegative constant which balances the relative merits of maximizing the fuzzy between-class scatter to the minimization of the fuzzy within-class scatter.

In real-world application of such face recognition, gene expression and web document recognition, the dimension M of the vector samples is usually large, so performing FDLPP by directly solving the eigenvectors of the M´M matrix S_b-aS_w is still computationally intensive. To reduce the computational demand, in this section, we present an efficient algorithm for performing FDLPP.

In the following, for the sake of simplicity, we assume that we deal with centered data. Suppose $\beta_1, \beta_2,\ldots, \beta_M$ are M orthonormal eigenvectors of total scatter matrix S_t and the first m (m = rank S_t) ones $\beta_1, \beta_2,\ldots, \beta_m$ are eigenvectors of S_t corresponding to positive eigenvalues and β_{m+1}, $\beta_{m+2},\ldots, \beta_M$ are eigenvectors of St corresponding to zero eigenvalues. Define the subspace $\phi_t = span\{\beta_1, \beta_2,..., \beta_m\}$ and its orthogonal complement can be denoted by $\phi^{\perp}_t = span\{\beta_1, \beta_2,..., \beta_m\}$ Obviously, $\phi^{\perp}_t$ is the null space of $S_t = S_b+S_w$.

Lemma 1: Lu *et al.* (2010) Suppose $\phi^{\perp}_t$ is the null space of S_t, then for every $\zeta \in \phi^{\perp}_t$, we have $\zeta^T x_i = 0$, i = 1, 2,..., N.

Theorem 1: Lu *et al.* (2010) Suppose $P = [\beta_1, \beta_2,\ldots, \beta_m]$ to be the matrix of all unit eigenvectors of S_t corresponding to nonzero eigenvalues and $u \in \mathbb{R}^{m\times 1}$ to be the eigenvector of the matrix $P^T(S_b-\alpha S_w)P$ corresponding to the eigenvalues λ. Then Pu is the eigenvector of the matrix $S_b-\alpha S_w$ corresponding to the eigenvalues λ.

Now, the algorithmic procedure of FDLPP is formally summarized as follows:

Step 1: Calculate the membership degree U
Step 2: Construct the fuzzy within-class weight matrix W_{fuzzy} and fuzzy between-class weight matrix B_{fuzzy} according to Eq. 3 and 5
Step 3: Calculate the fuzzy within-class Laplacian matrix L_{fuzzy} and fuzzy between-class Laplacian matrix H_{fuzzy} by Eq. 6-7
Step 4: Calculate the matrix P of all eigenvectors of S_t corresponding to positive eigenvalues
Step 5: Solve the eigenvalues problem of $P^T(S_b-\alpha S_w)$ Pu = λu, $u_1, u_2,\ldots, u_k$ are orthonormal eigenvectors corresponding to the k largest eigenvalues
Step 6: The optimal projection matrix is given by A = PU

EXPERIMENTS

To evaluate the performance of the proposed FDLPP method, we have performed experiments on ORL, Yale and FERET database. Experiments investigate the performance of the FDLPP algorithm over the reduced dimensions and compare it with the DLPP, DLMPP and other feature extraction algorithms. Experimental results demonstrate the accuracy of FDLPP over the variance of the dimensionality of subspaces. Figure 1 shows sample images of one person in ORL, FERET and Yale databases.

ORL database: The ORL database (AT and T Lab Cambridge) contains 400 face images of 40 individuals which were taken at different times, varying illustration and variations in facial expression. The total number of

Fig. 1: Samples of face image in ORL, FERET and yale face databases

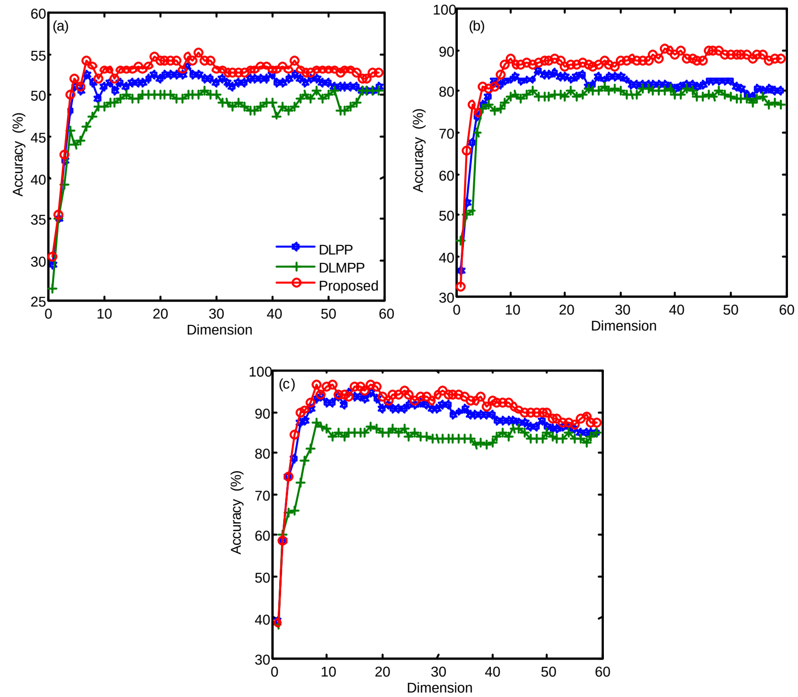

Fig. 2(a-c): Accuracies on ORL database with the variance of dimension (a) 4-Trains, (b) 5-Trains and (c) 6-Trains

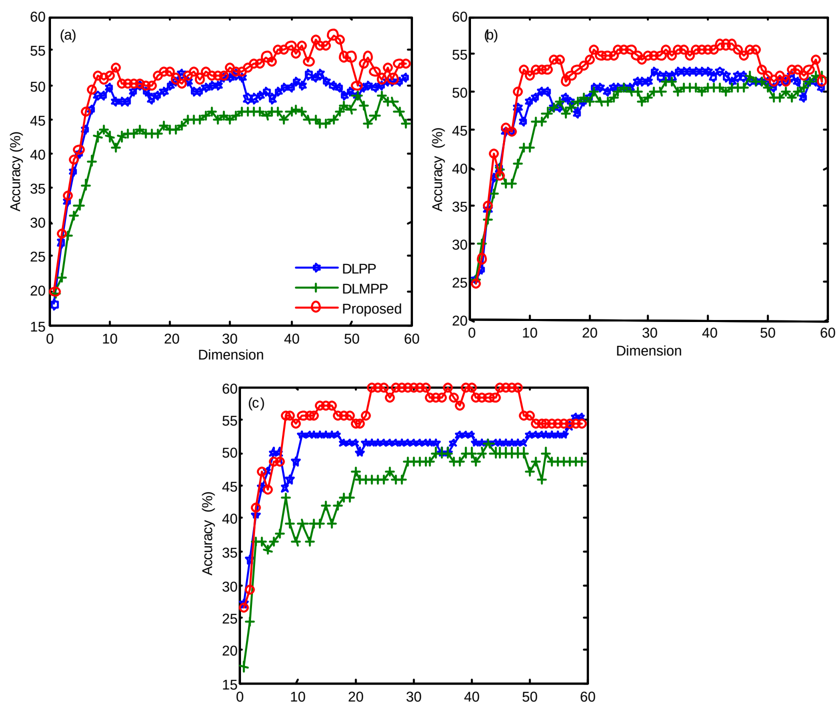

Fig. 3(a-c): Accuracies on FERET database with the variance of dimension (a) 3-Trains, (b) 4-Trains and (c) 5-Trains

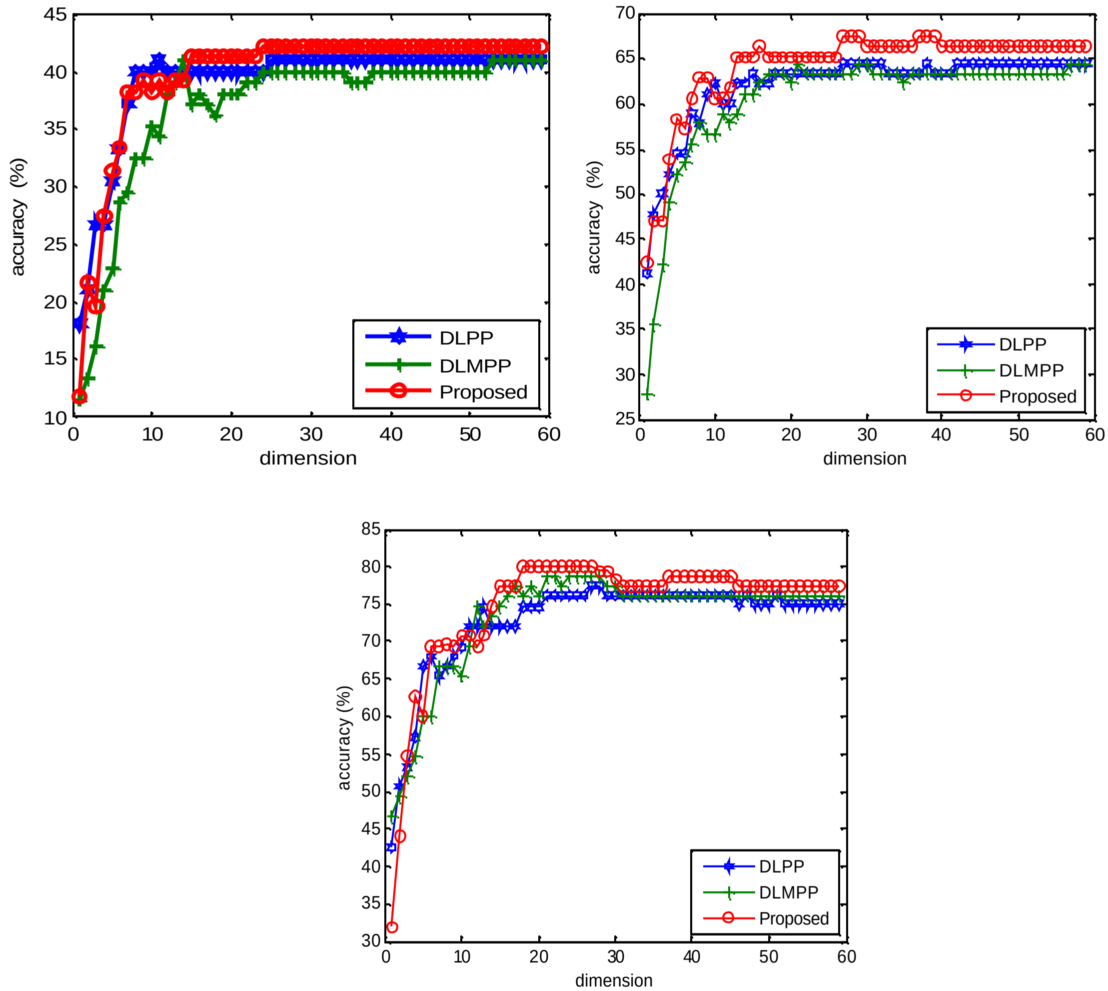

Fig. 4(a-c): Accuracies on Yale database with the variance of dimension (a) 4-Trains, (b) 5-Trains and (c) 6-Trains

images for each individual is 10. Each image was digitized and stored as an 112×92 pixel array whose gray levels ranged between 0 and 255. Each image in ORL database was manually cropped and resized to 65×60 in our experiments. The first l images (l varies from 4-6) of each individual are selected for training while the rest images are used for testing.

FERET database: The FERET database (Phillips *et al*., 2000) contains 1400 images of 200 individuals, each individual has seven images which were taken under unstable illumination, variations in facial expression.In our experiments, each image was manually cropped and resized to 60×60. The first l images (l = 3, 4, 5) of each individual are selected for training while the remaining images are used for testing.

Yale database: The Yale face database (Yale University, 2002) consists of 165 images from 15 individuals under various facial expressions and lighting conditions. Each individual has 11 images which was manually cropped and resized to 60×60. The first l images (l = 4, 5, 6) of each individual are selected for training and the remaining images are used for testing.

CONCLUSION

In this study, FDLPP method is proposed for feature extraction and face recognition. The fuzzy set theory is implemented to achieve the definition of the fuzzy Laplacian scatter matrix. The effect of the outlier's classification can be effectively reduced. The range both of the locality preserving between-class scatter S_b and the locality preserving within-class scatter S_w can be derived from the discriminant vector by MMC. Extensive experiments shown the improved accuracy and the reduced sensitivity to variations between face images caused by changes in illumination are superior to other feature extraction methods.

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