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Discriminant subspace learning constrained by locally statistical uncorrelation for face recognition

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ABSTRACT

High-dimensionality of data and the small sample size problem are two significant limitations for applying subspace methods which are favored by face recognition. In this paper, a new linear dimension reduction method called locally uncorrelated discriminant projections (LUDP) is proposed, which addresses the two problems from a new aspect. More specifically, we propose a locally uncorrelated criterion, which aims to decorrelate learned discriminant factors over data locally rather than globally. It has been shown that the statistical uncorrelation criterion is an important property for reducing dimension and learning robust discriminant projection as well. However, data are always locally distributed, so it is more important to explore locally statistical uncorrelated discriminant information over data. We impose this new constraint into a graph-based maximum margin analysis, so that LUDP also characterizes the local scatter as well as nonlocal scatter, seeking to find a projection that maximizes the difference, rather than the ratio between the nonlocal scatter and the local scatter. Experiments on ORL, Yale, Extended Yale face database B and FERET face database demonstrate the effectiveness of our proposed method.

1. Introduction

Face recognition (Belhumeur, Hespanha, & Kriengman, 1997; He, Yang, & Hu, 2005; Jiang, Mandal, & Kot, 2008; Liu, Cheng, Yang, & Liu, 1992; Wan, Sung, & Yau, 2010; Wang, Xu, Zhang, & You, 2010; Zhao, Chellappa, Phillips, & Rosenfeld, 2003) has attracted tremendous attentions in computer vision over the past last decades and many new techniques have been developed. The appearance based method is one of the most successful techniques. By using appearance based methods, an image is always represented by a high dimensional vector of pixels. To overcome the curse of dimensionality, a natural way is to learn a subspace in which we can detect the reduced intrinsic dimension in the high dimensional image space. PCA (Swets & Weng, 1996; Turk & Pentland, 1991) and LDA (Belhumeur et al., 1997) are two popular linear subspace algorithms for unsupervised and supervised learning, respectively. PCA projects data points onto a lower dimensional subspace, in which the sample variance is maximized. LDA computes a linear transformation which simultaneously maximizes the between-class scatter and minimizes the within-class scatter, achieving maximum discrimination.

However, PCA and LDA fail to explore essential structure of data. Recently, many researchers have shown that large amounts of high-dimensional data probably lie on a nonlinear manifold (Bengio, Paiement, & Vincent, 2003; Cai, He, & Han, 2007b; He, Cai, Yan, & Zhang, 2005; Kouropteva, Okun, & Pietikainen, 2003; Tenenbaum, de Silva, & Langford, 2000; Yan, Xu, Zhang, & Zhang, 2007). To address this problem, nonlinear dimension reduction techniques have been proposed to learn the nonlinear structure of the manifold, such as isometric feature (ISOMAP) (Belkin & Niyogi, 2003), locally linear embedding (LLE) (Roweis & Saul, 2000), and Laplacian Eigenmaps (LE) (Tenenbaum et al., 2000). This line of research is known as manifold learning which explores the inherent nonlinear structure hidden in the observation space. However, one of the limitations in many existing manifold learning methods is the out-of-sample problem (Bengio et al., 2003). To overcome the out-of-sample problem, Wang et al. proposed Neighborhood Preserving Embedding (NPE) (Wang et al., 2010) and Locality Preserving Projection (LPP) (He, Yanget al., 2005). Both algorithms aim to preserve local structure of data but differ in that NPE is a nonlinear learning for data embedding and LPP is based on linear transformation that is actually performing linear dimension reduction.

The above manifold criterion is applied to Fisher criterion and MFA (Yan et al., 2007) as well as local Fisher discriminant analysis (LFDA) (Sugiyama, 2006), nonparametric discriminant analysis (NDA) (Li, Lin, & Tang, 2009), semi-supervised Discriminant Analysis (SDA) (Cai, He, & Han, 2007a), local discriminant projection (LDP) (Zhao, Sun, Jing, & Yang, 2006), Semi-UDA (Qiu, Lai, & Chen, 2008) local discriminant embedding (LDE) (Chen, Chang, & Liu,

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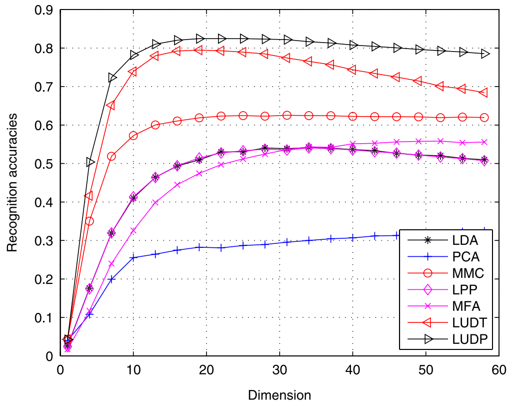

Fig. 19. Average recognition rate versus reduced dimensionality on FERET database.

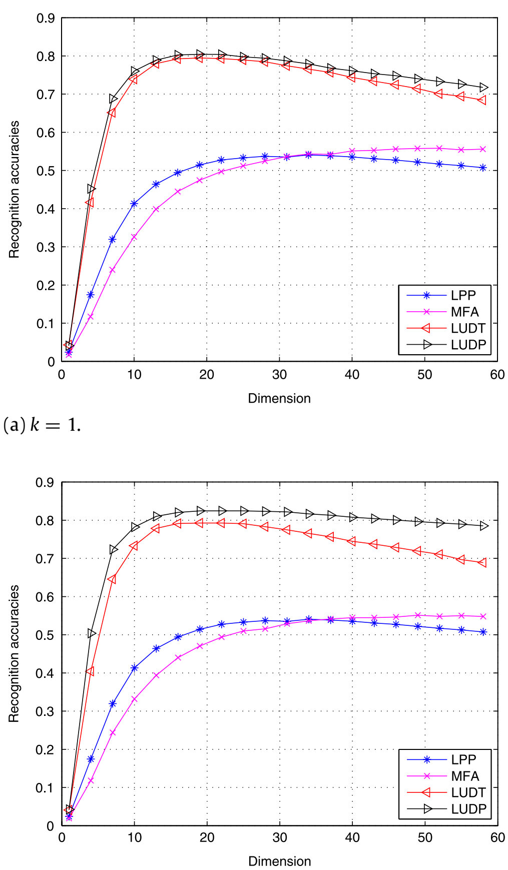

Fig. 20. Average recognition rate versus reduced dimensionality on FERET database with $l = 3$ and $k(=1, 2)$.

4.5. *Experiments on FERET dataset*

In this subsection, we test the proposed method on the FERET face database. In our experiment, for each individual, we randomly selected 3 samples for training, and the rest were used for testing. The best average recognition rate and the corresponding standard deviations over 10 runs of tests are shown in Table 6. Fig. 19 illustrates the plot of recognition rate against the number of features used in the matching for PCA, LDA, LPP, MMC, MFA, LUDT and LUDP. Fig. 20 displays the performance of the LUDT, MFA and LUDP algorithms over the reduced dimensions and the value of the nearest neighbors k.

Table 6
The average recognition rate (%) and the standard deviations (%) on FERET database.

Methods	PCA	LDA	MMC	LPP	MFA	LUDT	LUDP
Recognition rate (%)	44.40	54.90	63.06	54.81	56.70	80.22	83.03
Std. (%)	0.88	1.84	1.75	1.92	2.13	1.24	0.96

5. Conclusion

Uncorrelated features of minimum redundancy are highly desirable in feature reduction for face recognition. In this paper, we present a novel subspace projection method for dimensionality reduction and feature extraction. We call this new development the locally uncorrelated discriminant projections (LUDP). By introducing a suitable constraint into the objective function, we can iteratively calculate the optimal discriminant vectors under the corresponding uncorrelated constraints. By maximizing the difference between non-local scatter and the local scatter, LUDP can also address the small sample size problem. Moreover, the weights between two nodes of a graph are adjusted according to their class information and local information, which can explore the intrinsic structure of original data and improve the recognition ability. Experimental results on ORL, Yale, Extended Yale face database B and FERET database indicate that the LUDP method performs better than other related methods such as PCA, LDA, MMC, LPP, MFA and LUDT in terms of classification accuracy.

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