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Marginality Preserving Embedding for Robust Face Recognition

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One of the fundamental problems in pattern recognition is the curse of dimensionality in data representation. Many algorithms have been proposed to find a compact representation of data as well as to facilitate the recognition task. In this paper, we propose a novel dimensionality reduction technique called Marginality Preserving Embedding (MPE). Unlike Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) which projects data in a global sense, MPE seeks for local structure in the manifold. This is similar to other subspace learning techniques but the difference with them is that MPE preserves marginality in local reconstruction. Experimental results show that the proposed method provides better representation in low dimensional space and achieves lower error rates in face recognition.

Keywords : Dimensionality Reduction, Manifold Learning, Marginality Preserving Embedding (MPE).

1. INTRODUCTION

In many applications of computer vision and machine learning we often need to deal with very high dimensional data but the intrinsic structure of the data may lie in a low dimensional space. Learning such high dimensional data is computationally expensive and not suitable for all practical applications. Moreover, it is also desirable to reduce the dimension for visualization. But this low dimensional data must preserve the underlying structure of high dimensional data in order to be of use. This leads researchers to develop methods of dimensionality reduction that can extract manifold structure of data on which data may reside.

Many techniques for dimensionality reduction have been proposed over the last few decades [1-5]. All these methods have validated one thing in common-recognition rate can significantly be improved at low dimensional subspace. Two of the most primitive techniques for this purpose are PCA [1-3] and Linear Discriminant Analysis [2-5]. PCA transforms original image space to orthogonal feature space in the sense of mean square error. LDA seeks for linear transformations that minimize within class covariance and maximize between class covariance matrices. Unlike PCA, LDA encodes discriminating features in a linearly separable space that are not necessarily orthogonal [6]. When number of training data is small, PCA can outperform LDA but if the class information is available LDA can be used to find optimal subspace for optimal discrimination [7].

Recently various research [6, 8-10] on face images have shown that data may reside in a nonlinear sub-manifold. As a result manifold learning techniques becomes popular for face recognition. Some popular nonlinear techniques include Laplacian Eigenmap [11], Locally Linear Embedding (LLE) [8] and Isomap. All these methods showed impressive results on artificial datasets and some real applications. But they are defined only on training

Table 1
Face Recognition Results (%) on ORL Database.

Method	2 Samples	5 Samples
Baseline	71	89
Eigenfaces	53	75.14
Fisherfaces	74.6	91.52
LPP	69.22	87.28
NPE	76.04	92.38
MPE	79.51	94.64

Table 2
Face Recognition Results (%) on Yale Database.

Method	2 Samples	5 Samples
Baseline	73.33	84.25
Fisherfaces	73.93	89.69
LPP	73.33	83.64
NPE	75.04	88.48
MPE	78.78	90.30

Performance of this method is demonstrated through several experiments and it shows lower error rate in face recognition.

REFERENCES

1. He X, Yan S Hu, Y Niyogi P and Zhang H. Face Recognition using Laplacianface, *IEEE Trans. Pattern Analysis and Machine Intelligence*, 27(3): 328-340, 2005.
2. Roweis S and Saul L. Nonlinear Dimensionality Reduction by Locally Linear Embedding. *Science*, 290: 2323-2326, 2000.
3. He X, Cai D, Yan S and Zhang H. Neighborhood Preserving Embedding, *Proceedings of* 11^{th} *International Conf. on Computer Vision ICCV 05*, 2005.
4. He X and Niyogi P. Locality Preserving Projections, *Advances in Neural Information Processing Systems MIT Press*, 16, 2003.
5. Belkin M and Niyogi P. Laplacian Eigen maps and Spectral Techniques for Embedding and Clustering, *Proc. Conf. Advances in Neural Information Processing Systems,* 15, 2001.
6. Tanenbaum J, Silva V and Langford J. A Global Geometric Framework for Nonlinear Dimensionality Reduction, *Science*, 290(22): 2319-2323, 2000.
7. Lin Y, Liu T and Chen H. Semantic Manifold Learning for Image Retrieval, *Proc.* 13^{th} *Ann. ACM Int'l Conf. Multimedia*, 2005.
8. Yan S, Xu D, Zhang B, Zhang H, Yang Q and Lin S. Graph Embedding and Extensions: A General Framework for Dimensionality Reduction, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 29(1):40-51, 2007.
9. He X, Cai D and Han J. Learning a Maximum Margin Subspace for Image Retrieval, *IEEE Trans. on Knowledge and Data Engineering*, 20(2):189-201, 2008.
10. Joliffe I. Principal Component Analysis, *Springer-Verlag*, 1986.
11. Belhumeur P, Hespanha J and Kriegman D. Eigenfaces vs. Fisherfaces: Recognition using Class Specific Linear Projection, *IEEE Trans. on Pattern Analysis and Machine Intelligence,* 19(7):711-720, 1997.