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A structure-preserved local matching approach for face recognition

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ABSTRACT

In this paper, a novel local matching method called structure-preserved projections (SPP) is proposed for face recognition. Unlike most existing local matching methods which neglect the interactions of different sub-pattern sets during feature extraction, i.e., they assume different sub-pattern sets are independent; SPP takes the holistic context of the face into account and can preserve the configural structure of each face image in subspace. Moreover, the intrinsic manifold structure of the sub-pattern sets can also be preserved in our method. With SPP, all sub-patterns partitioned from the original face images are trained to obtain a unified subspace, in which recognition can be performed. The efficiency of the proposed algorithm is demonstrated by extensive experiments on three standard face databases (Yale, Extended YaleB and PIE). Experimental results show that SPP outperforms other holistic and local matching methods.

1. Introduction

Within the past decades, face recognition has drawn a lot of attention for its immense potentials in many applications e.g., military, commercial, law enforcement and human–computer interaction. Face recognition can be defined as the identification of individuals from their face images by using a stored database of faces labeled with people's identities (Hakan et al., 2005). This is a very challenging and complex task because the appearances of individual's face features are always affected by illumination conditions, aging, poses, facial expressions and disguises (Zhao et al., 2003). Moreover, the performances of face recognition algorithms are also impaired by some other problematic factors such as noise and occlusion.

Recently, many researchers have developed numerous algorithms for face recognition (Zhao et al., 2003). Among these approaches, appearance-based subspace analysis methods are well studied. These methods have a common characteristic in finding a low-dimensional feature subspace from the original high-dimensional face space. They operate directly on images or appearance of face objects, and are effective for face feature extraction and representation (Hu, 2008). Currently, the most representative subspace techniques for face recognition are principal component analysis (PCA) (Turk and Pentland, 1991), Fisher linear discriminant analysis (LDA) (Belhumeur et al., 1997), non-negative matrix factorization (NMF) (Lee and Seung, 2000) and locality preserving projections (LPP) (He et al., 2005).

PCA is the method which projects the original data into a low-dimensional subspace spanned by a set of mutually orthogonal basis vectors. The basis vectors which capture the directions of maximum variance in the data are obtained from the eigenvectors of the covariance matrix corresponding to the largest eigenvalues. In (Turk and Pentland, 1991), the set of basis vectors obtained by PCA was called Eigenfaces and then used to describe face images. However, PCA does not take any class information of the input data into account, which may weaken the recognition performance. In order to overcome this limitation, LDA is developed for face recognition (Belhumeur et al., 1997). LDA is a supervised subspace analysis technique, which searches for the optimal projection directions that are most effective for discrimination. By applying LDA, we can get a subspace in which the samples of different classes are more discriminative and the samples of the same class are tighter. The algorithm using LDA to describe face images is called Fisherfaces. Unlike PCA and LDA, NMF is designed to capture part-based structures inherent in the face images space (Lee and Seung, 2000). The non-negative constraints introduced in NMF do not allow negative elements either in the basis vectors or weighted vectors, which can effectively extract part-based representation of face images with low feature dimensionality. LPP is a newly proposed subspace analysis algorithm (He and Niyogi, 2003). The remarkable advantage of LPP is that it is a manifold learning based method and can find the intrinsic low-dimensional nonlinear manifold structure hidden in observation space. The method using LPP to describe face images is named Laplacianfaces (He et al., 2005). More recently, some extensions of the LPP algorithm were also

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proposed for face recognition (Yang et al., 2009; Xu et al., 2010; Wang et al., 2010). Experimental results showed that these extended algorithms can overcome the limitations of the original LPP and achieved better recognition performances.

In contrast to above holistic subspace analysis methods which directly use whole face images as the input patterns, some local matching techniques show more promising results in face recognition tasks (Zou et al., 2007). The general idea of local matching methods is to first locate several facial sub-patterns, and then classify the faces by comparing and combining the corresponding local features. In (Rajkiran and Vijayan, 2004), a modular PCA (ModPCA) method was proposed for face recognition. ModPCA firstly divided the whole face images into several smaller sub-images, and then applied PCA to all sub-image blocks for local feature extraction. Chen and Zhu (2004) proposed a similar approach called sub-pattern PCA (SpPCA). In SpPCA, the whole face images were also firstly partitioned into a set of equally-sized sub-patterns in a non-overlapping way. Then, PCA was performed on each of sub-pattern sets which share the same original feature components for feature extraction. Tan and Chen (2005) realized that different sub-patterns of the human face may have different contributions to recognition. Thus, the SpPCA method was extended to adaptively weighted sub-pattern PCA (Aw-SpPCA). In Aw-SpPCA, the weight of each sub-image block to recognition was determined by the discriminative ability of samples in the corresponding sub-pattern set. Geng and Zhou (2006) made a similar observation as Tan and Chen, and proposed a framework, named Selective Ensemble of Image Regions (SEIR), for local matching based face recognition. However, they chose to select several sub-patterns from all possible candidates instead of weighting them. Recently, a SubXPCA algorithm was presented (Kumar and Negi, 2008). In SubXPCA, the local features computed by SpPCA were balanced against the global viewpoint of PCA, and the cross-correlations across sub-patterns were considered. Besides PCA, some other techniques were also used for local matching based face recognition. A weighted Sub-Gabor algorithm was proposed in (Loris and Dario, 2007). In this method, the local facial features were extracted by a bank of Gabor filters and Karhunen–Loeve transforms, and then a Parzen window classifier was used for recognition. Zhu (2007) proposed a sub-pattern non-negative matrix factorization (SpNMF). In this algorithm, he performed NMF decomposition on each sub-image set divided from the whole face and showed that the SpNMF performs better than the original NMF for face recognition. More recently, a supervised local matching approach termed local ridge regression (LRR) was presented for face recognition (Xue et al., 2009). LRR incorporated both label information and local matching techniques into the recognition process. Thus, it can obtain significantly higher recognition accuracy than classical Eigenfaces and Fisherfaces algorithms.

Though the local matching algorithms discussed above can effectively deal with the face images with pose, direction of lighting and facial expression variances (Zou et al., 2007), they still suffer from the following limitations. Firstly, most existing local matching methods extract local facial features from each sub-pattern set independently, and ignore the relationship among sub-patterns from the same original data. Recently, some researchers have shown that the holistic context and configural relationship of the face are very important for recognition (Pawan et al., 2006; Sadr et al., 2003). Therefore, in order to improve the recognition performances of local matching approaches, the structure relationship among the sub-patterns of each face image should be taken into account (Calder et al., 2000). Secondly, the feature extraction techniques used in the above local matching methods cannot preserve the nonlinear manifold structure of the sub-pattern set. Some researchers have shown that not only whole faces, but also the sub-patterns of them lie on a smooth low-dimensional manifold (Saul and Roweis, 2000; Roweis et al., 2000; Tenenbaum et al., 2000; Belkin and Niyogi, 2003). Thus, manifold learning based methods are more suitable to characterize the intrinsic nonlinear or curved structure of the sub-pattern sets.

In this paper, a structure-preserved projections (SPP) algorithm is presented for face recognition. Compared with the existing local

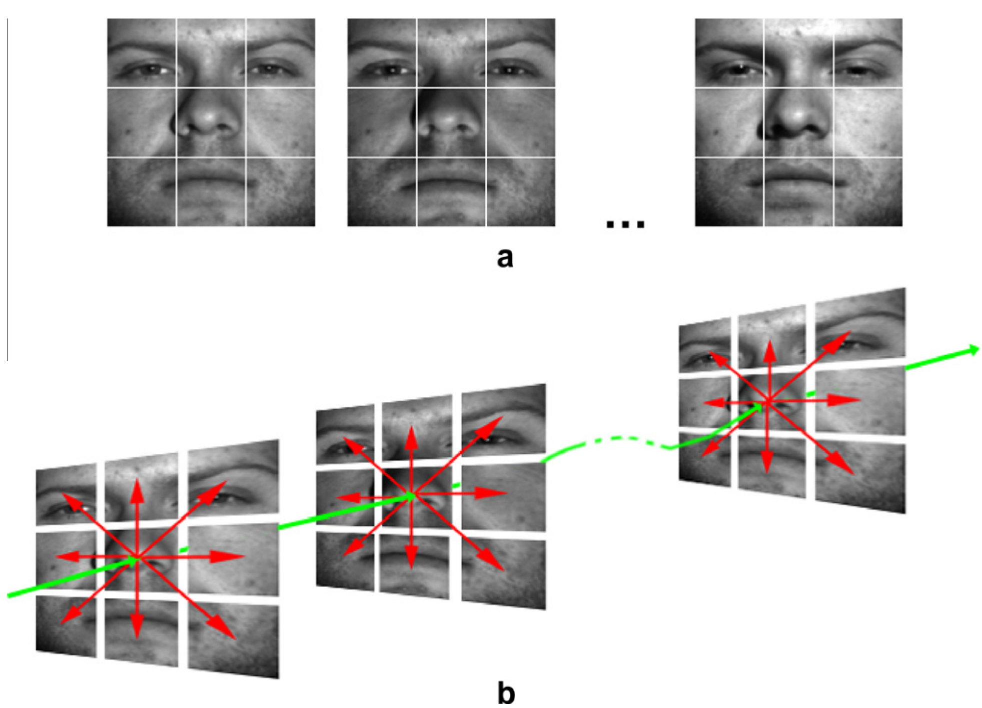

Fig. 1. An intuitive illustration of SPP: (a) the partitioned face images and (b) for each sub-pattern, the purpose of SPP is to preserve the configural structure between it and the rest sub-patterns of the same face (red lines), and the non-linear structure of the sub-patterns sharing the same original feature components of it (green line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)