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Geometric Preserving Local Fisher Discriminant Analysis for person re-identification

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ABSTRACT

Recently, Local Fisher Discriminant Analysis (LFDA) has achieved impressive performance in person re-identification. However, the classic LFDA method pays little attention to the intrinsic geometrical structure of the complex person re-identification data. Due to large appearance variance, two images of the same person may be far away from each other in feature space while images of different people may be quite close to each other. The linear topology exploited in LFDA is not sufficient to describe this nonlinear data structure. In this paper, we assume that the data reside on a manifold and propose an effective method termed Geometric Preserving Local Fisher Discriminant Analysis (GeoPLFDA). The method integrates discriminative framework of LFDA with geometric preserving method which approximates local manifold utilizing a nearest neighbor graph. LFDA provides discriminative information by separating different labeled samples and pulling the same labeled samples together. The geometric preserving projection provides local manifold structure of the nonlinear data induced by graph topology. Taking advantage of the complementary between them, the proposed method achieves significant improvement over state-of-the-art approaches. Furthermore, a kernel extension of the GeoPLFDA method is proposed to handle the complex nonlinearity more effectively and to further improve re-identification accuracy. Experiments on the challenging iLIDS, VIPeR, CAVIAR and 3DPeS datasets demonstrate the effectiveness of the proposed method.

1. Introduction

Person re-identification, which aims at matching people across multiple non-overlapping camera networks, has attracted huge interest over the recent decades [1]. It manages to achieve that when a target disappears from one camera, he/she can be re-identified in another camera deployed far away. It can save a lot of human efforts on exhaustively searching for a target from large amounts of video sequences [2].

In the literature, the methods of re-identification can be divided into two categories: feature extraction and metric learning. Feature based approaches [3,4] focus on extracting distinctive visual features to represent the human appearance. Metric learning [5–7] approaches aim at finding an optimal metric that can maximize the distance of samples from different class whilst minimize the distance of samples from the same class. Our approach belongs to the latter category.

Typical metric learning approach such as Large Margin Nearest Neighbor (LMNN) [5,6] tries to learn a metric that minimizes the distance between each training point and its k nearest similarly labeled neighbors, while maximizing the distance between all differently labeled points. Inspired by LMNN, a bunch of metric learning methods for person re-identification have been proposed, such as ITML [8], RDC [9], PCCA [10], KISSME [11], LFDA [7,12,13].[1] While these methods could achieve encouraging re-identification performance, they are limited by linearity and prone to overfitting especially in large scale and high dimensional learning scenarios.

Traditional metric learning approaches [5–8] often assume that data is linearly distributed, which does not hold true in re-identification. Samples in the same class may undergo dramatic appearance variations due to changes in view angle, illumination, background clutter and occlusion [14] (see Fig. 1). Meanwhile, samples of different people may share similar appearance, e.g., people wearing clothes with similar color or similar pattern.

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[1] Though not clarified in the literature before, LFDA learns a projection to measure the distance between samples, which can be seen as learning a low rank metric. In this sense, we category it as metric learning method for re-identification.

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0925-2312/

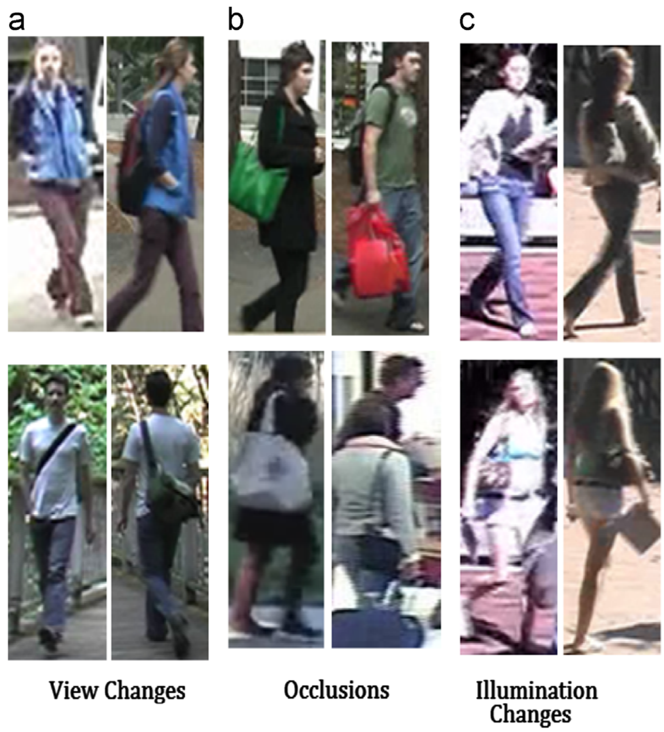

Fig. 1. Example for person re-identification challenges such as viewpoint changes, occlusions and illumination changes.

Therefore, traditional linear topology is not sufficient to model the re-identification data.

Furthermore, the metric learning methods are prone to overfitting because of the small sample size (SSS) problem in person re-identification, i.e. the number of samples per subject is far less than the dimension of the feature. For instance, the VIPeR dataset [15] only contains two images of each subject, while the dimension of features is usually thousands or higher. In this case, metric learning methods tend to overfit because pair or triplet-based constraints become much easier to satisfy in a high-dimensional space and thereby lead to poor generalization performance. The absence of regularization further deteriorates recognition performance [16]. As for LFDA, the within-class scatter matrix $\boldsymbol{S}^W$ cannot be accurately estimated because the number of within-class samples is very limited thus $\boldsymbol{S}^W$ often becomes singular. The singularity can easily lead to overfitting.

Motivated by these problems, in this paper, we propose a novel algorithm termed Geometric Preserving Local Fisher Discriminate Analysis (GeoPLFDA) which makes a reasonable assumption that the re-identification data reside on a manifold and each sample corresponds to a point on the manifold. The method exploits local manifold approximation derived by nearest neighbor graph [17]. This graph topology provides better approximation to the real world data structure than linear assumptions. To accommodate with LFDA, the data is then projected into a low dimensional linear subspace following the criterion that geometric information should be well preserved. In other words, nearby points on the manifold are mapped to nearby points in the subspace, and faraway points to faraway points. LFDA is performed to improve the intra-class compactness and inter-class separation. Through a linear weighted technique, the geometric preserving techniques are effectively incorporated into the LFDA scheme. In this way, not only the discriminant information is exploited, the geometrical structure is also effectively preserved. The geometric preserving term can serve as a regularization term thus overfitting is alleviated. What's more, the proposed GeoPLFDA incorporates global information from the whole feature data which makes up for the fact that the discriminative margin in LFDA is determined by limited nearby data pairs [18]. In addition, we propose the kernel extension of GeoPLFDA which handles the complicated nonlinear high dimensional data structure more effectively. Experimental results demonstrate the effectiveness of the proposed method.

The main contribution of the proposed method is three-folds:

- A more faithful representation of the data structure is proposed, which assumes that the data lies on a nonlinear manifold.
- The proposed method not only exploits discriminant structure utilizing techniques from LFDA, but also effectively incorporates local structure information by constructing the nearest neighbor graph.
- A closed form solution is achieved through generalized eigenvalue decomposition. Hence, complex iterative optimization schemes are not required.

The rest of the paper is organized as follows: a brief view of related works is presented in Section 2. Section 3 introduces the proposed GeoPLFDA algorithm and its kernel extension. Experimental results on iLIDS, VIPeR, CAVIAR and 3DPeS datasets are presented in Section 4. Finally, the concluding remarks and suggestions for future work are discussed in Section 5.

2. Related work

2.1. Person re-identification

Existing person re-identification methods can be roughly divided into two categories.

Feature based approaches focus on designing a feature representation that can be both distinctive and robust to large appearance variations. For instance, Farenzena et al. [3] try to utilize a strategy to extract distinctive and stable features. This strategy is based on the localization of perceptual relevant human parts, driven by asymmetry/ symmetry principles. Color Hexagonal-SIFT and Color Histogram Features (CHF) are exploited in [19] to establish a multi-camera handoff system for person re-identification. Liu et al. [20] model the relevance among multiple image features by mutual information. Liu et al. [21] propose an unsupervised approach to bottom-up feature importance mining on-the-fly specific to each probe image. In addition to appearance based features, Liu et al. [22] integrate gait biometric into the descriptor for person re-identification, which can handle color distortion and other appearance variations.

Many metric learning and matching schemes are proposed for person re-identification. Dikmen et al. [6] develop a variant of LMNN by introducing a rejection option to the unfamiliar matches (LMNN-R). The key idea of Information Theoretic Metric Learning (ITML) [8] is to search for a solution that satisfies the constraints while being close to a distance metric prior $\boldsymbol{M_0}$, i.e. the identity matrix for the Euclidean distance. Zheng et al. [9] treat person re-identification as a Relative Distance Comparison problem (RDC). The method aims to maximize the likelihood of a pair of true matches having a relatively smaller distance than that of a wrong match pair in a soft discriminant manner. Mignon et al. [10] introduce an algorithm termed Pairwise Constrained Component Analysis (PCCA) for learning distance metrics from sparse pairwise similarity/dissimilarity constraints. Hirzer et al. [11] propose a metric learning approach called Keep It Simple and Straightforward (KISSME), which addresses the metric learning approach form a statistical inference point of view. An et al. [23] propose a hypergraph based matching scheme which discovers both pairwise and higher order relationships between the probe and the