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Cauchy estimator discriminant analysis for face recognition

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ABSTRACT

With the rapid development of computer vision and pattern recognition, face recognition, one of the basic research topics in computer vision and pattern recognition, has received intensive attention in recent years. Usually, traditional face recognition algorithms have considerable discriminant ability; however, when there are some samples that are easy to confuse in the face database, the discriminant ability of traditional face recognition algorithms will inevitably decrease. In this paper, based on the patch alignment framework (PAF) and Cauchy estimator theory, we proposed a novelty subspace learning algorithm for face recognition named Cauchy estimator discriminant analysis (CEDA). Under the framework of PAF, both local and global geometries of the input samples are preserved; by using the Cauchy estimator, large errors caused by samples that are easy to confuse could be overcome. We conducted the experiments on three face databases and strongly illustrated the effectiveness of CEDA for face recognition.

1. Introduction

Face recognition, one of the most popular areas in computer vision, has many particular real world applications, such as human face tracking detection, face positioning, security surveillance, and so on. In the past several decades, the process of the face recognition algorithm has experienced two main generations corresponding to the basic method and linear subspace method for face recognition.

In the early work, a basic method such as Eigenface or Fisherface was usually adopted for face recognition. Eigenface was first proposed by Turk et al. [5] in 1991; by using this method, we obtain the eigenvectors of a set of faces; furthermore, these eigenvectors make up the Eigenface, which represents the important features, such as eyes, ears, noses and so on. However, although Eigenface is optimal for reconstruction of a face, it may not be optimal for discrimination information. In 1997, Belhumeur et al. [24] proposed Fisherface for face recognition. The advantage of Fisherface is that the optimal subspace is obtained by maximizing the ratio of between to within class scatter matrices. However, although Fisherface is optimal for discrimination information, it is not ideal for discriminating faces near the individual boundaries.

Currently, the linear subspace method, which contains two stages corresponding to sparse representation and manifold learning for face recognition, is usually adopted for face recognition. The first stage of the linear subspace method is sparse representation [19,25–28]. Sparse Regularization Discriminant Analysis (SRDA) [25] is a typical linear subspace method based on sparse representation; it preserves the sparse representation structure of the feature space. Firstly, SRDA constructs a concatenated dictionary; then, the sparse representation structure is learned under the dictionary; finally, by using the learned sparse representation structure as a regularization term of Linear Discriminant Analysis, SRDA considers both the sparse representation structure and the discriminating efficiency. Cui et al. [28] proposed a novelty linear subspace method based on joint sparse representation; the proposed method aims to adopt two sparse regularization terms to utilize the sparse and structure priors of a face feature, giving the model better discriminative ability in video-based face recognition. For one individual, there are several face images taken from different angles, under different lightings and with different expressions. However, the traditional global linear method struggles to achieve good performance, especially for a face database containing samples that are easy to confuse. Then, in the second stage, we use a powerful dimensional reduction tool, called manifold learning, to obtain the potential essence structure of face images in a high dimensional feature space. For manifold learning, a popular framework named the patch alignment

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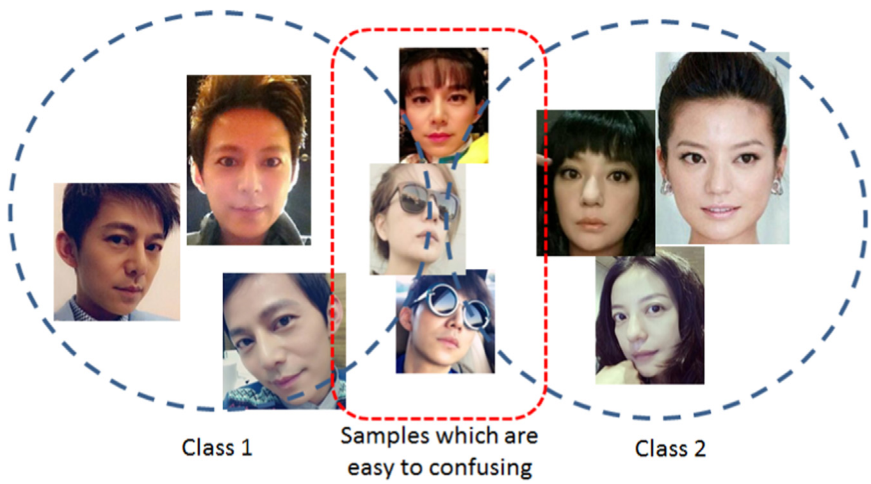

Fig. 1. Different classes of face images in different blue circles; in the middle red rectangle, there are some between-class samples that are easy to confuse in the face database. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

framework (PAF) [2], which well interprets the difference between different manifold learning algorithms, is usually adopted for face recognition to increase discriminant ability, considering not only the local structure but also global structure.

In fact, most of the samples in the face database are affected by the change of light and angles and whether there are glasses. Under these conditions, the difference between samples within-class will become large, while the difference between samples between-class will become small; those affected samples are usually easy to confuse during recognition. Fig. 1 presents this phenomenon; there are two classes of face images corresponding to the two blue circles, and due to being affected by the change of light and angles and whether there are glasses, some face images within-class are far away, while some between-class are very small. In Fig. 1, the images in the red rectangle are samples that are easy to confuse; although they are in different classes, the differences are very small.

In this paper, we propose a new subspace learning algorithm based on manifold learning for face recognition named Cauchy estimator discriminant analysis (CEDA); the framework of PAF is applied to preserve local and global geometry information, and the theory of Cauchy estimator is utilized because it can overcome the error when there are some training samples that are easy to confuse.

The rest of this paper is organized as follows. In Section 2, related works on subspace learning that are important for face recognition and the experiment section are reviewed. We present the proposed CEDA algorithm in Section 3. Section 4 shows the experimental results using the FERET database, UMIST database and YALE database. Finally, conclusions about the proposed algorithm are presented in Section 5.

2. Related work

In the previous section, we have quickly reviewed the development of face recognition over the past several decades. As a general rule, the features are usually in the high dimensional space when extracted from the original data. Due to the curse of dimensions in face recognition, the dimensional reduction (or subspace learning) algorithm is a very important step that can effectively transition features from the high dimensional space into a low dimensional subspace. Over the past decades, many dimensional reduction algorithms [7,10,11,13,14,17,31–39] have been proposed. We divided those dimension reduction algorithms into two categories based on geometry structure: globally linear dimensionality reduction algorithms [21,22,29,30] and manifold learning-based dimensionality reduction algorithms [3–6].

The most famous globally linear dimensionality reduction algorithms are, for example, Principle component analysis (PCA) [8] and Linear Discriminant Analysis (LDA) [7,9]. PCA is an unsupervised learning method that does not use class label information. The objective of PCA is to maximize the mutual structure between original high-dimensional samples and Gaussian distributed and transformed low-dimensional samples. The PCA method does not perform very well because it does not add the label information. LDA is a typically supervised algorithm that takes label information into consideration. LDA tries to minimize the trace of the within-class scatter matrix and maximize the trace of the between-class scatter matrix to find discriminates between different classes. However, LDA suffers from some problems, such as neglecting local geometry structure, being unable to address small sample size (SSS) [15] and a projection matrix that is likely singular.

Manifold learning is also popular for learning the local and global intrinsic structures. Therefore, many researchers have utilized manifold learning in their new algorithms [7,10,12]. Locally linear embedding (LLE) [10] utilizes linear coefficients to reconstruct high dimensional space training samples; those coefficients are also suitable for reconstruction in low dimensional embedding. Laplacian Eigenmaps (LE) [7] preserve the geometry relationships by using an undirected neighbor relations weighted graph. Both LLE and LE learning algorithms suffer from the out of sample problem [20]. Discriminative Locality Alignment (DLA) [2] is also a supervised manifold learning algorithm. DLA overcomes the above problems by controlling local and global geometry information. In the stage of local patch, DLA aims to preserve the discriminative information through the classification optimization criteria such that the distance between the within-class samples is as small as possible and the distance between between-class samples is as large as possible. In the global stage, DLA integrates all the weighted part optimizations to form a whole subspace structure. However, all of these algorithms ignore the error recognition due to samples that are easy to confuse.

3. Cauchy estimator discriminant analysis

In this paper, we research the supervised dimensional reduction learning method; thus, we have both class label and samples information. We take local and global geometry information into