Optik 167 (2018) 7–14

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Original research article

A weighted sparse neighbor representation based on Gaussian kernel function to face recognition

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ARTICLE INFO

Article history:
Received 22 March 2017
Accepted 14 December 2017

Keywords:
Sparse representation
Face recognition
Weighted nearest neighbor
Gaussian kernel function

ABSTRACT

Currently, sparse representation was widely used in face recognition. However, traditional sparse representation method cannot effectively consider the effect of different weight of training samples When reconstruct the test samples. In this paper, a weighted sparse neighbor representation based on Gaussian kernel function model is presented to resolve above problems. Firstly, K nearest training samples is selected for constructing a new training dictionary according to the Euclidean distances between the test samples and training samples. Then, a weight is given to each sparse coefficient of new training sample. Above sparse coefficient is solved by norm L1 minimization method. Finally, recognition task is performed by the minimum reconstruction error of sparse coefficient. Experimental results illustrate that, the proposed algorithm achieves 96.64% correct recognition rate, which is significantly higher than the various existing comparison methods.

1. Introduction

With the rapid development of face recognition, it has become a hotspot of computer vision and biometric features recognition [1–4]. Face recognition technology has a broad application prospect in security, identity recognition, the company attendance, remote monitoring, etc. Currently, the face recognition is a hot point of research in universities and research institutions. In the past few decades, many researchers have proposed some face recognition algorithms. The most typical method is the Principal Component Analysis algorithm (PCA) [5] and Linear Discriminant Analysis algorithm (LDA) [6–7]. The PCA and LDA algorithm are used for dimension reduction; it can achieve great effect in face recognition. LDA is also used for the method of reducing dimension. First of all, the high-dimensional samples were projected to the best discriminant vector subspace. Then training samples can be classified according to largest distance between classes and the smallest distance in the same class, to achieve the purpose that extract classification information and compress feature space dimension. In recent years, many new face recognition algorithms have been proposed. For example, reference [8] proposed a study of Similarity Measures with Linear Discriminant Analysis for Face Recognition. P. Huang et al. [9] proposed an adaptive linear discriminant regression classification for face recognition. H. Li et al. [10] introduced a robust face recognition based on dynamic rank representation. B. Liu et al. [11] proposed a face recognition using class specific dictionary learning for sparse representation and collaborative representation. W. Gong et al. [12] proposed an enhanced Asymmetric Bilinear Model for Face Recognition. Y. Jiang et al. [13] introduced a multiclass AdaBoost ELM and Its Application in LBP Based Face Recognition.

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https://doi.org/10.1016/j.ijleo.2017.12.072
0030-4026/

Of late years, the sparse representation algorithm has been applied in the field of face recognition, face recognition algorithm based on sparse representation get a high recognition rate [14–15] (Sparse Representation based Classification, SRC). In view of the sparse representation theory, the basic principle of the SRC is to use the same face of the linear correlation. The contributions of the samples can be reflected in the coefficients of the sparse representation, then reconstruct the designated test sample. In the linear combination, the training sample coefficient which is the same as test sample is not zero, and the probability of non-zero is also high, and other training sample coefficient generally is zero or close to zero. It means in the low-dimensional space, samples from the same class are tight, while samples from different classes are far apart. Hence, the reconstruction sparse coefficients can be considered as a measurement of comparability.

Motivated by this opinion, many new face recognition algorithms have been developed by researchers based on traditional sparse face recognition algorithms. For example, Y. Du et al. [16] proposed generating virtual training samples for sparse representation of face images and face recognition. In this article, they view the multiplication of two images of the face as a virtual face image to expand the training set and devise a representation-based method to perform face recognition. By multiplying a training sample with another sample from the same subject, it strengthens the facial contour feature and greatly suppresses the noise, but it increase the time of the experiment and the uncertainty of training data. So the performance was limited to some extent. Z. Liu et al. [17] introduced a face Recognition via Weighted Two Phase Test Sample Sparse Representation. It took the whole training sample to construct a dictionary, and it was an unsupervised method. D. Tang et al. [18] proposed a novel sparse representation method based on virtual samples for face recognition. This paper proposed method first form a new training set by adding random noise to extends the training samples and then performs face recognition. Because the noise is random, the experimental result is uncertain. L. Qiao et al. [19] proposed a sparsity preserving projections with applications to face recognition. SPP aims to preserve the sparse reconstructive relationship of the data, and the authors pointed out that robust to noises to some extent. However, SPP took the whole training sample to construct a dictionary, and it did not consider the influence of the nearest neighbor samples on the test samples. C. Lan et al. [20] proposed an Orthogonal Sparsity Preserving Projections for Feature Extraction. OSPP has more powerful sparsity preserving ability than SPP and hence OSPP has better classification performance. So OSPP has the same drawbacks as SPP. Z. Lai et al. [21] proposed a Global Sparse Representation Projections for Feature Extraction and Classification. GSRP can be considered as a fused of sparse representation and manifold learning. The experiment of GSRP will take a long time. k neighbor classification algorithm [22–23] have been widely used in pattern recognition, machine learning and computer vision and others areas.

Traditional face recognition algorithms based on sparse representation do not take into account the weight of each training sample of test samples, which causes recognition rate decline [24]. The k neighbor classification algorithm, as a pattern recognition technique, had been applied extensively in face recognition. The dimensionality of face images is usually very high and the number of samples is less than that of dimensions, which cause the low computational efficiency of sparse representation methods. Dimensionality reduction gives an effective way to avoid the curse of dimensionality.

To solve above two problems, a weighted sparse neighbor representation based on Gaussian kernel function to face recognition is developed in this paper. There are two main contributions to be considered in this paper:

1) Reconstruct a new training sample dictionary by$k$neighbor classification algorithm. The principal component analysis (PCA) algorithm was used for face feature dimension reduction. This reduces the computation complexity in feature matching. Then, pick out k nearest training sample to reconstruction new training sample dictionary before solving sparse coefficient.
2) Weight sparse coefficients by Gaussian kernel function. Calculate the distances between each training samples and test samples based on the Gaussian kernel function to obtain weighting matrix$W$. This Matrix is used to adjust the training samples matrix. This step had considered fully the importance of the similarity between training samples and test sample. Experimental results show that this method can obtain higher recognition rate compared with the traditional sparse face recognition algorithm.

The rest of this paper is organized as follows: A sparse neighbor representation based classification for face recognition is given in Section 2. Section 3 describes the weighted sparse neighbor representation based classifier for face recognition. Experimental results are presented and discussed in Section 4. Finally, Section 5 makes a summary of this paper.

2. Sparse neighbor representation based classification for face recognition

Sparse representation was originally applied on compression perception problem in the field of signal processing. Sparse description methods get rapid development in face recognition since J. Wright's published the first paper about sparse description for face recognition [27]. The purpose of sparse representation is decomposing image signal into an atomic linear combination. The basic idea of sparse algorithm is shown as follows: Firstly, complete the training dictionary. It is consisted of face image which has been classified. Secondly, normalize the columns of training dictionary to have unit L_2 –norm. Thirdly solve sparse coefficient with norm L_1 minimization. Fourthly, compute each residual of each class. Finally, output recognition results of test sample.

Test samples can be expressed by linear combination of training dictionary. However, traditional sparse face recognition algorithms ignore the significance of the representative category of training samples which are very similar to test samples.