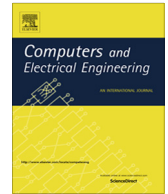




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Vector projection for face recognition [☆]

Changhui Hu ^{a,b}, Mengjun Ye ^c, Yijun Du ^{a,b}, Xiaobo Lu ^{a,b,*}^a School of Automation, Southeast University, Nanjing 210096, China^b Key Laboratory of Measurement and Control of Complex Systems of Engineering, Ministry of Education, Southeast University, Nanjing 210096, China^c College of Mechatronics and Control Engineering, Hubei Normal University, Huangshi 435002, China

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ABSTRACT

In this paper, a novel approach for face recognition is proposed by using vector projection length to formulate the pattern recognition problem. Face images of a single-object class are more similar than those of different-object classes. The projection length of a test image vector on the direction of a training image vector can measure the similarity of the two images. But the decision cannot be made by only a training image which is the most similar to the test one, the mean image vector of each class also contributes to the final classification. Thus, the decision of the proposed vector projection classification (VPC) algorithm is ruled in favor of the maximum combination projection length. To address the partial occlusion problem in face recognition, we propose a local vector projection classification (LVPC) algorithm. The experimental results show that the proposed VPC and LVPC approaches are efficient and outperform some existing approaches.

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1. Introduction

As the great application prospects in commerce, law enforcement, information security, etc. [1–4], face recognition has received significant attention in the past twenty years. Especially in recent years, a tremendous amount of new methods, new technologies and new principles have emerged in an endless stream in face identification literature. These methods can be divided into two categories: the geometry based methods and the appearance based methods [5]. The appearance based methods have become the dominant approaches for face recognition, and most appearance based approaches have been proposed to improve the face recognition rate using manifold learning methods.

Turk and Pentland [6] proposed the Eigenfaces method, which is one of the significant approaches in early face recognition literature. It adopts principal component analysis (PCA) to compute the facial feature space (i.e. the optimal projection matrix), and then the facial feature can be evaluated by projecting a face image into the facial feature space, which is used for the final classification. The projection idea of the Eigenfaces has a huge impact on its following face identification technologies. Belhumeur et al. [7] proposed the Fisherfaces method, which applies Fisher's linear discriminant (FLD) to compute the facial feature space. As the Fisherfaces contains the class specific discriminatory information, it provides better performance than the Eigenfaces, yet suffers from the small sample size problem [7,8]. In contrast with the Eigenfaces and Fisherfaces being based on one-dimensional (1D) image vector, two important approaches are proposed based on two-dimensional (2D) image matrix: one is the Two-dimensional PCA (2DPCA) method [9], and the other is the Two-dimensional FLD (2DLDA)

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* Corresponding author at: School of Automation, Southeast University, Nanjing 210096, China.

E-mail address: xblu2013@126.com (X. Lu).

method [10]. The two methods directly deal with the 2D face images without image to vector transformation, which are not only more computationally efficient than the Eigenfaces and Fisherfaces, but also avoid the small simple size problem of the Fisherfaces. In the Eigenfaces, Fisherfaces, 2DPCA and 2DLDA, the facial features are obtained by projecting face images into the facial feature space, thus these approaches can be termed as the classical facial feature based methods for face recognition.

Beside the classical facial feature based methods, other features can also be used for face recognition. Hafed and Levine [11] proposed the discrete cosine transform (DCT) based method. Some significant DCT coefficients are selected to characterize a face image for face recognition, which can be termed as the DCT feature of the face image. Ahonen et al. [12,13] proposed the local binary pattern (LBP) based method. The LBP operators are assigned to represent a face image for face identification, which can be termed as the LBP feature of the face image. Cevikalp et al. [14] proposed the discriminative common vector (DCV) based method for face recognition. A common vector can be obtained by using the images of the same object class, and the eigenvectors corresponding to the nonzero eigenvalues of the scatter matrix of the common vectors compose the optimal projection matrix of the DCV (i.e. the DCV feature space). Recently, Gaidhane et al. [15] proposed the common eigenvalue (CEV) based method. The polynomial coefficients of the covariance matrix of a face image are designated as its facial feature (i.e. the polynomial coefficient feature for a face image). The nullity of the polynomial coefficients-based companion matrices of two face images is used as the similarity measure for face recognition. Gao et al. [16] proposed the two-dimensional maximum local variation (2DMLV) method for face recognition, which estimates the variation of pixel values of images by using the image Euclidean distance (i.e. the local variation feature for a face image). But the 2DMLV causes computation issues when the training sample size (or the image size) is large.

However, the downsampled based methods without feature extraction have received much attention in recent years. Wright et al. [17] proposed the sparse representation classification (SRC) method. All the downsampled training images are normalized to compose an overcomplete dictionary during the training session, and a test image can be represented as a sparse linear combination of all the elements in the overcomplete dictionary. Then the SRC's sparse coefficient vector can be calculated by standard linear programming methods. Naseem et al. [18] proposed the linear regression classification (LRC) method, which is based on the concept that face image vectors in the same class lie on a linear subspace. A test image can be represented as a linear combination of the training images in the same class, and the LRC's coefficient vector is computed by using least-squares estimation.

As mentioned above, the main drawback of the facial feature based methods is that they have to carry out complex training process which consumes a lot of computational time, and these approaches are not conducive to process a large number of training face images in practical applications. Although the downsampled based methods do not need to execute complex training process, downsampled images may lose some discriminative information for face identification, and the coefficient vector of a linear combination is difficult to obtain especially the training sample size is large. To address aforementioned issues, we propose a simple but efficient vector projection based approach for face recognition without considering feature extraction and the image dimensionality.

In this paper, we propose a novel vector projection classification (VPC) approach for the problem of face identification. Face images of a single-object class are more similar than those of different-object classes, and the vector projection length can evaluate the similarity between two image vectors in the face image vector space. In the proposed VPC approach, the most similar training image and its corresponding class mean image are used to decide the final classification, which is ruled in favor of the maximum combination projection length. To address the partial occlusion problem in face recognition, we propose a local vector projection classification (LVPC) algorithm. Compared with the state-of-the-art approaches, the proposed VPC approach is more simple and efficient since only vector projection is needed without feature extraction or coefficient vector computation.

This paper is organized as follows. In Section 2, the mathematical principle of the VPC is presented, and the proposed VPC and LVPC algorithms are described in details. Section 3 gives the experimental results using six public face databases, and finally Section 4 concludes this paper.

2. Vector projection for face recognition

Since face images have similar structure, the face images of the same person have more similarities than those of different persons. In this section, we propose vector projection for face recognition. Firstly, we present the mathematical principle of the VPC approach, secondly the VPC algorithm is proposed and compares with the traditional Eigenfaces method in detail, and finally we present the LVPC algorithm to address the partial occlusion problem in face identification.

2.1. Mathematical principle of vector projection classification

As the images from the same object class have the most similarities, therefore, the two most similar images probably belong to a single-object class in face recognition. It is a proverbial fact that a vector contains two attributes which are length and direction in the vector space. Intuitively, the more similar the two face images are, the longer the projection length between the two image vectors is in the image vector space. Thus the projection length between two image vectors can be used to evaluate the similarity of two images. The mathematical principle of vector projection is described as following.

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