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A new face recognition method based on image decomposition for single sample per person problem

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ABSTRACT

The image decomposition based method is one of the efficient and important face recognition solutions for the single sample per person problem. The low image decomposition performance and the unconvincing reconstruction of the approximation image are the two main limitations of the previous methods. In this paper, a new single sample face recognition method based on lower-upper (LU) decomposition algorithm is proposed. The procedure of the proposed method is as following. First, the single sample and its transpose are decomposed to two sets of basis images by using the LU decomposition algorithm, which is more efficient than the image decomposition algorithms of the previous works. Two approximation images are reconstructed from the two basis image sets by the reverse thinking approach based on experimental analysis. Then, the fisher linear discriminant analysis (FLDA) algorithm is used to evaluate the optimal projection space by using the new training set consisting of the single sample and its two approximation images for each person. Finally, the nearest neighbor classifier based on Euclidean distance is adopted as the final classification. We make two main contributions: one is that we propose to decompose the single sample and its transpose using the efficient LU decomposition algorithm, and reorder each basis image set according to the basis image energy; the other is that we present a reverse thinking approach based on experimental analysis to reconstruct the approximation image. The performance of the proposed method is verified using four public face databases, namely FERET, AR, ORL and Yale B. The experimental results indicate that the proposed method is efficient and outperforms several state-of-the-art approaches which are proposed to address the single sample per person problem.

1. Introduction

Face recognition has great application prospects in access control, smart card, passport, information security, person identification, surveillance, etc. [1–3]. Many researchers from different nations had done a lot of studies and achieved many significant results in face recognition, however, some tough problems have not been well solved, such as the so-called single sample per person problem [3,4]. The performance of the face recognition system is affected by the number of training samples [5–7], hence, when only one training image per person (i.e. single sample per person) is available, the face recognition problem becomes more challenging. Recently, many approaches have been proposed to address the single sample per person problem, which can be roughly divided into three categories according to the information of the recognition model based on learning as briefly reviewed in the following.

The first category is the virtual image based methods [8–11], which learns the discriminant information from the single sample and its virtual images. In [8], the hybrid-eigenfaces method was proposed for single sample per person problem, and virtual images of the single sample under different poses and illuminations were generated by using hybrid global linear regression. In [9], the component-based linear discriminant analysis method was proposed, and virtual images were generated by moving each face image component along four directions. In [10], the singular-value-perturbed version principal component analysis method (or SPCA+ method for brevity) was presented, and virtual images were obtained by SVD perturbation. In [11], virtual images with pose, illumination and expression variations were generated by rendering the recovered 3D face model. In general, all above methods need prior knowledge to generate new virtual images. However, the quality and reality of the generated virtual images cannot be guaranteed.

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The second category is the generic set based methods [3,12,13,14], which learns both the within-class and between-class variations of persons in the single sample set (it consists of the single sample of each training object) by using a generic set containing multiple samples for each person. In [3], the adaptive discriminant analysis method (or ADA method for brevity) was proposed, and the within-class variations of each single sample were inferred by learning the generic set. In [12], the adaptive linear regression method was proposed, and the within-class variations of each single sample adaptively pulled from the single sample's kNNs (i.e. k nearest neighbors of the single sample) in the generic set. In [13], the Pseudo-Fisherface method was presented, and the generic set was directly used to calculate the within-class and between-class variations for persons in the single sample set. In [14], the extended sparse representation classification method (or ESRC method for brevity) was proposed, and the overcomplete dictionary consisted of the single sample set and the intra-class variations of persons in the generic set. Generally speaking, all above methods employ a generic set to infer the within-class variations of persons in the single sample set. However, the discriminant model learned from the generic set is more suitable to identify the persons of the generic set than those of the single sample set.

The third category is the single sample based methods [1,2,15,16], which learns the recognition model by making full use of the information of the single sample itself. In [15], the partition-FLDA method was proposed for the single sample per person problem, and each single sample was partitioned into a set of non-overlapping sub-image blocks, to construct a new training sub-set for each class. In [16], the uniform pursuit approach was proposed, and the neighboring information was employed to obtain more discriminative low dimensional feature representation. Besides aforementioned single sample based methods, one of the fairly simple but efficient solutions for single sample per person problem is the image decomposition based method, and two typical approaches are reported in [1,2].

Fisher linear discriminant analysis (FLDA) is a widely used subspace analysis method in face recognition, and aims to find a projection matrix which can be able to separate the images of different persons as far as possible and compress the images of the same person as compact as possible. Comparative studies between FLDA and principal component analysis (PCA) are reported independently in [17,18], in which FLDA outperforms PCA significantly in face recognition. However, the drawback of FLDA is that it requires a large number of training images for good generalization due to the singular problem of the within-class scatter matrix [1]. In [19], a two-dimensional FLDA (2D-FLDA) algorithm for feature extraction was proposed, which could deal with the 2D image without image to vector transformation. The 2D-FLDA algorithm not only has higher computational efficiency, but also avoids the singular problem of the within-class scatter matrix. In the case of the single sample per person problem, the FLDA algorithm can be a failure because the within-class scatter matrix is zero. Several approaches have been proposed to make the FLDA applicable to the single sample per person problem, two of the efficient and important approaches are presented in [1,2].

In [1], the singular value decomposition (SVD) based method (or SVD-based method for brevity) was proposed. The single sample is decomposed into a set of basis images by SVD, and then the 3 most significant basis images corresponding to the 3 largest singular values are used to reconstruct an approximation image. The single sample and its approximation image are used to calculate the within-class scatter matrix. It is reported that the SVD-based method outperforms all the methods in [13,15,20], which are proposed to overcome the single sample per person problem in face recognition. In [2], the orthogonal triangular with column pivoting (QRCP) decomposition based method (or QRCP-based method for brevity) was proposed. The single sample is decomposed to a set of basis images by QRCP decomposition, and then the approximation image containing at least 97% of the whole energy of the original image is reconstructed by the several most significant basis images. Using the same way, the approximation image of the transpose of the single sample can be reconstructed. It is reported that the QRCP-based method performs better than the SVD-based method in terms of recognition rate and training time.

However, the main drawback of the SVD-based and QRCP-based methods is that the reconstruction of the approximation image is unconvincing. For the SVD-based method, the 3 most significant SVD basis images are used to reconstruct an approximation image, the reason of choosing 3 is that the difference between the approximation image and the original image is very small when the number of basis images is bigger than 4. For the QRCP-based method, the number of basis image is determined such that an approximation image contains at least 97% of the whole energy of the original image, but it is not explained that why 97% is selected. Thus, exploring a reasonable method for the reconstruction of an approximation image can raise the performance of the image decomposition based method. The motivation of this work is based on the fact that it is required to improve both the image decomposition speed and recognition rate of the image decomposition based method for the single sample per person problem in face recognition.

In this paper, we propose a new face recognition method based on LU decomposition algorithm to address the single sample per person problem. The single sample and its transpose are decomposed to two sets of basis images by the efficient LU decomposition algorithm, and two approximation images are reconstructed from the two basis image sets respectively by the reverse thinking approach based on experimental analysis. The single sample and its two approximation images are used to calculate the optimal projection space of the 2D-FLDA algorithm for feature extraction and final classification. We make two main contributions: one is that we propose to decompose the single sample and its transpose by the efficient LU decomposition algorithm, and reorder each basis image set according to the basis image energy; the other is that we present a reverse thinking approach based on experimental analysis to reconstruct the approximation image.

This paper is organized as follows. The procedure of the 2D-FLDA is briefly reviewed in Section 2. Section 3 presents the proposed method in details. Section 4 gives the experimental results, and finally Section 5 concludes this paper.

2. Two-dimensional FLDA

In this section, the 2D-FLDA algorithm is briefly presented. The important mathematical notations used in this paper are presented in Table 1.

The 2D-FLDA algorithm [19] directly calculates the within-class scatter matrix and between-class scatter matrix from the 2D image matrix without image to vector transformation. It not only has higher computational efficiency, but also avoids the singular problem of the within-class scatter matrix. The 2D-FLDA aims to separate the images of different objects as far as possible and compress the images of the same object as compact as possible.

The goal of 2D-FLDA algorithm attempts to find the optimal projection matrix $W=[w_1, w_2, \dots w_l] \in \mathrm{R}^{m \times l}$ (l is at most $\min(C-1, n)$ [2]) to maximize the criterion as follows:

$$J(W)=\frac{\left|W^T S_b W\right|}{\left|W^T S_w W\right|} \tag{1}$$

where superscript "T" denotes matrix transpose, the within-class scatter matrix S_w and the between-class scatter matrix S_b are