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Random projection-based partial feature extraction for robust face recognition

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ABSTRACT

In this paper, a novel feature extraction method for robust face recognition (FR) is proposed. The proposed method combines a simple yet effective dimensionality increasing (DI) method with an information-preserving dimensionality reduction (DR) method. For the proposed DI method, we employ the rectangle filters which sum the pixel values within a randomized rectangle window on the face image to extract the feature. By convolving the face image with all possible rectangle filters having various locations and scales, the face image in the image space is projected to a very high-dimensional feature space where more discriminative information can be incorporated. In order to significantly reduce the computational complexity while preserving the most informative features, we adopt a random projection method based on the compressed sensing theory for DR. Unlike the traditional holistic-based feature extraction methods requiring the time-consuming data-dependent training procedure, the proposed method has the partial-based and data-independent properties. Extensive experimental results on representative FR databases show that, as compared with conventional feature extraction methods, our proposed method not only achieves the higher recognition accuracy but also shows better robustness to corruption, occlusion, and disguise.

1. Introduction

Face recognition (FR) has been a very popular topic in computer vision research for several decades [1–10]. Recently FR has been successfully applied to a wide range of applications, such as biometric identity authentication, human computer interaction, and intelligent surveillance. As an indispensable procedure in FR, the feature extraction method remains to be investigated due to various challenges including illumination change, facial expression variation, and noise, such as corruption, occlusion, and disguise, etc.

The subspace analysis-based dimensionality reduction (DR) methods, such as principal component analysis (PCA) [1], linear discriminant analysis (LDA) [2], and independent component analysis (ICA) [3], have been employed to project the face image in high-dimensional image space into a low-dimensional subspace. In the subspace, the face can be represented more compactly, thereby helping to remove those aforementioned change, variation, and noise. The PCA determines the basis vectors by finding the directions of the large variance in data [1]. Then the extracted basis vectors are used to construct a measurement matrix, namely the projection matrix, for DR. Unlike the PCA that best describe the data, the LDA searches for the basis vectors in the underlying subspace that can best discriminate the data among classes [2]. As a generalization of PCA, ICA aims to find the independent nonorthogonal basis vectors [3] which reconstruct the data better than PCA in the presence of noise.

However, the conventional subspace analysis-based feature extraction methods can only achieve the limited performance in FR task [3–8]. The reasons are: first, the direct projection from the image space to a subspace cannot extract the most discriminative information for classification. Second, the most representative structural information in the image space may not be preserved due to the inherent property of the DR method [1,2]. Third, the illumination change or the expression variation, existing in the original image space, is retained by the conventional DR method. In contrast, recent research work emphasizes the importance of the high-dimensionality feature in FR task. In [9], the dense facial landmark-based multiscale feature sampling has been proposed to extract the high-dimensional feature for high performance FR. Liu et al. [10] and Zhao et al. [11] showed that mapping the face image from the input space to the high-dimensional feature space through Gabor filters helps to incorporate more discriminative information for better FR. Moreover, the works [12–15] on other image classification problems also reveal the significance of the high-dimensional feature. Yang et al. [12] showed that the over-completed high-dimensional representation is more separable, and Sanchez et al. [13] reported on the necessity of high-

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dimensional features in large-scale image classification. Pooling in spatial [14] and feature spaces [15] also lead to the higher dimensionality and the better performance.

In addition, the aforementioned subspace analysis-based DR methods require the data-dependent training procedure, which makes the FR system inefficient [16,17]. When face images are added or deleted in the FR system, these methods inevitably need to re-compute the projection matrix, which requires the update of all face images. Random projection (RP) [16–21], as a newly emerged DR method, has attracted more attention due to its efficiency and data-independent property. In RP, no training samples are required to calculate the projection matrix since it can be generated beforehand. Since the subspace estimated by RP is independent of the samples and their dimension, RP does not require the update of the projection matrix when the data changes. The RP has been successfully applied to the feature extraction for texture classification [19]. The RP-based DR method also has been used to obtain the prominent performance on object tracking [20]. Moreover, it has been reported in [21] that RP can achieve the comparable performance as the PCA-based Eigenfaces method in FR. However, the research of the more accurate and robust RP-based feature extraction method remains to be an open issue.

Moreover, most adopted features for FR are holistic-based features, such as Eigenfaces [1], Fisherfaces [2], Laplacianfaces [22], and variants [4,5]. It has been shown that these features are sensitive to the various types of noise such as occlusion, corruption and disguise. In contrast, the partial-based facial features [23–28], such as patches around eyes or nose, are more efficient and robust than the holistic-based ones. Savvides et al. [24] showed that the partial feature is more discriminative than the holistic-based one in FR. Seo et al. [25] and Jun et al. [26] illustrated that the local features are very robustness to facial images variations in terms of robust FR. Heisele et al. [27] demonstrated that the facial component-based representation is superior to the holistic-based one. Zhu et al. [28] illustrated the effectiveness of the multiscale patch-based collaborative representation for FR.

In this paper, motivated by these aforementioned works, we propose a novel partial-based feature extraction method which combines a simple yet effective dimensionality increasing (DI) method with an information-preserving DR method. For the proposed DI method, we employ the rectangle filters which sum the pixel values within a randomized rectangle window on the face image to extract the feature. By convolving the face image with all the possible rectangle filters having various locations and scales, the face image in the image space can be projected to a very high-dimensional feature space where more discriminative information can be incorporated. In order to significantly reduce the computational complexity while preserving the most informative features, a random projection method based on the compressed sensing theory is adopted for DR. To further enhance the FR performance, a multi-radius local binary pattern (MLBP)-based image representation method is also proposed. Unlike the traditional holistic-based feature extraction method requiring the time-consuming data-dependent training procedure, the proposed method has the data-independent properties. Furthermore, the proposed feature extraction method can be easily synthesized as a single measurement matrix which fuses the aforementioned DI and DR procedures. Thus it is very efficient to generate the measurement matrix since this matrix is independent of the training dataset and just needs to be computed only once offline.

The rest of the paper is organized as follows. Section 2 presents and analyzes the proposed feature extraction method. Section 3 performs experiments and Section 4 concludes the paper.

2. Proposed method

The proposed feature extraction method primarily consists of three parts as shown in Fig. 1. The original face image is first represented by using the proposed MLBP to incorporate more structural information. Then the MLBP image vector will be mapped to a very high dimensional space by the proposed DI method to further incorporate discriminative information for better classification. Finally, the DR is adopted for facilitating practical application while preserving the salient information of face image in the aforementioned very high dimensional space. Some notations used in this paper are summarized in Table 1.

2.1. MLBP representation

The local binary pattern (LBP) [29,30], the local gradient pattern (LGP) [26], the local directional number pattern (LDN) [31], and the local phase quantization (LPQ) [32] are the local appearance descriptors being able to extract the structural facial feature in FR. In this paper, for obtaining more structural information of the

Table 1
Summary of some notations used in this paper.

Notation	Description
$\mathbf{x} \in R^m$	Transformed image vector with dimension m
$\mathbf{y} \in R^n$	Extracted feature vector with dimension n
$\mathbf{p}_i \in R^m$	Rectangle filter with dimension m
$\mathbf{P} \in R^{L \times m}$	Rectangle filter matrix
$\mathbf{R} \in R^{n \times L}$	Random projection matrix
$\mathbf{M} \in R^{n \times m}$	Measurement matrix

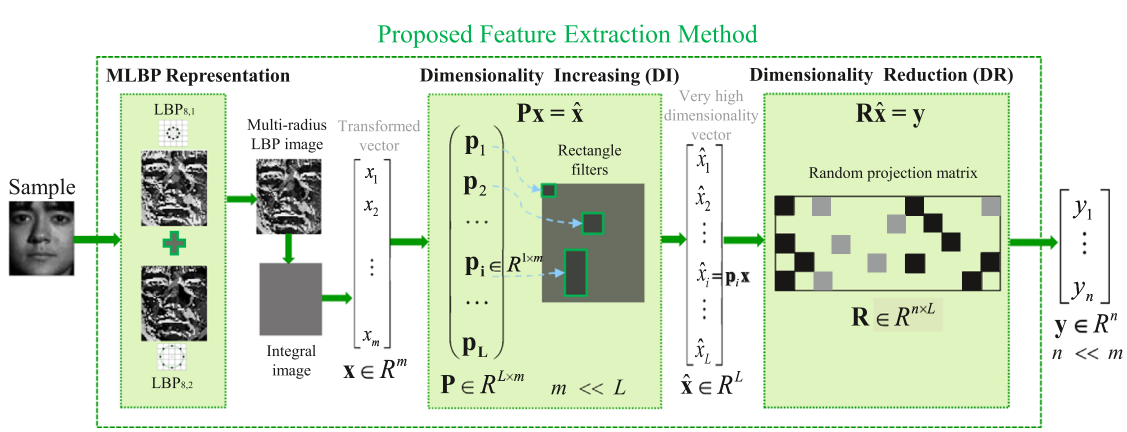

Fig. 1. Overview of the proposed feature extraction method.