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Robust iris recognition using sparse error correction model and discriminative dictionary learning

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ABSTRACT

Robust iris recognition is a hot research topic in the biometrics community and the sparse representation-based methods are promising to achieve desirable robustness and accuracy. Motivated by the fact that corruptions and occlusions incurred by eyelash occlusions, eyelid overlapping, specular and cast reflection in iris images are spatially localized but large in magnitude, we present a robust iris recognition method based on a sparse error correction model. In the proposed method, all the training images are concatenated as a dictionary and the iris recognition task is cast to an optimization problem to seek a sparse representation of the test sample in terms of the dictionary. And a sparse error correction term is introduced into the objective function of the optimization problem to deal with gross and spatially localized errors. Furthermore, in order to compact the huge dictionary, we introduce a discriminative dictionary learning framework to reduce computational complexity. Experimental results on CASIA Iris Image Database V3.0 show that the proposed methods achieve competitive performance in both recognition accuracy and efficiency.

1. Introduction

Iris recognition is one of the most reliable and secure methods for personal identification and authentication [1], which has been attracted an increasing attention in the past two decades. Two most well-known and representative iris recognition frameworks were developed by Daugman [2] and Wildes [3]. Daugman [2] applied a 2-D Gabor filter to extract the features from the scale-normalized iris images and quantized them to 256 bytes iris codes. Then, the normalized Hamming distance between the iris codes was employed as the measure for recognition. In contrast, Wildes [3] used convolution with Laplacian of Gaussian filter at multiple scales to produce a template of the iris texture and then computes the normalized correlation as the similarity metric. Motivated by their pioneer works, a lot of iris recognition algorithms have been presented to pursue more excellent performance. The earlier works were summarized in [1] and some recent efforts were reported in [5–10]. Existing iris recognition algorithms based on feature extraction and matching have achieved very high recognition accuracy for clean iris images [4].

However, the quality of the acquired iris images is often poor in practical scenarios due to various side effects such as motion blur, defocus blur, eyelid overlapping, specular and cast reflection. This leads to heavy performance degradation for most existing methods so far [1,5]. Improving the robustness of the iris recognition algorithm is still a challenging issue in the iris biometric community. Si et al. [8] focused on the robustness of iris segmentation and developed an eyelash detection algorithm based on directional filters to enhance the iris segmentation, achieving promising results. Li and Ma [9] presented a robust method based on the Random Sample Consensus (RANSAC) to localize the non-circular iris boundaries and an image registration method based on the optical flow algorithm to account for iris image deformation. Instead of the traditional feature extraction and matching framework, Pillai et al. [10] proposed a novel framework based on random projection and sparse representation-based classification (SRC) [11]. This method achieves desirable robustness to blur, segmentation error and small level occlusions. However, when the level of occlusions is relatively high, the recognition rate of the algorithm decreases remarkably. Moreover, the SRC algorithm requires a sufficiently large number of training images from each class to span subspace of each class and stacks all training images to form a dictionary directly, which leads to a large size of dictionary and intensive computation complexity.

In this paper, we firstly present an improved SRC iris recognition method based on sparse error correction (SEC) mode [11] to

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improve the robustness of the recognition algorithm to the high level occlusions and corruptions. The extra robustness derived from the SEC mode comes from the presence of a sparse error term which corresponds to the occlusions and corruptions of the iris image. Since the errors incurred by occlusions, secularities and cast shadows are large in magnitude but sparse in space, it is more reasonable that a test sample is better represented by a combination of the training samples with additive sparse and large-magnitude errors than by the standard SRC model used in [10]. Furthermore, a discriminative dictionary learning method for sparse error correction model (SEC-DKSVD) derived from discriminative K-SVD (D-KSVD) [12] is introduced to compact dictionary to improve both the efficiency and accuracy of the iris recognition algorithm. Finally, in order to detect and reject those invalid test images, we propose a validation scheme based on the cumulative sparsity concentration index (CSCI) [10]. Differing from [11,10] in which SCI of the recovered sparse representation coefficient vector was applied as the confidence of the recognition result, the suggested CSCI-based strategy employs SCI of the label vector obtained by the learned classifier. Besides the ability of detecting and rejecting the invalid samples, this scheme improves the robustness of iris recognition as well.

The rest of the paper is organized as follows. In Section 2, the adaptability of the SR-based method for iris recognition task is discussed, and the proposed sparse error correction model for iris recognition is presented. In Section 3, the improved discriminative dictionary learning method for error correction model is introduced. In Section 4, the validation scheme for recognition results is suggested. Experimental results are reported in Section 5, and we conclude the paper in Section 6.

2. Sparse error correction model for iris recognition

Recently, Wright et al. [11] reported a powerful tool, the SRC algorithm, for face recognition. SRC depends on low-dimensional linear models for illumination variation in recognition tasks. The SRC algorithm relies on low-dimensional linear models for illumination variation in recognition tasks. More specifically, given n training samples $d_{i,1}, d_{i,2}, \ldots, d_{i,n} \in R^m$ of the ith class object, the new test sample $y_i \in R^m$ of this object will lie near the linear span of the training samples

$$y_i = d_{i,1}x_{i,1} + d_{i,2}x_{i,2} + \cdots + d_{i,n}x_{i,n} \quad (1)$$

where $x_{i,1}, x_{i,2}, \ldots, x_{i,n} \in R$ are the scalar coefficients, varying from one test sample to the next. This approximate low-dimensional linear model is inspired by the theory that the images of a rigid, Lambertian object under varying illumination lie near a 9-dimensional linear subspace [13]. However, since the iris is neither a rigid nor a Lambertian object, a natural question would be: does this phenomena hold for iris images? To answer this, we choose 120 classes (eyes) from CASIA Iris Image Database V3.0 (CASIA-IrisV3) [14], 18 images for each class. The publicly available code of Masek and Kovesi [15] is used to segment irises. The iris samples from the ith subject are concatenated to form a matrix $D_i = [d_{i,1}|d_{i,2}|\cdots|d_{i,n}]$. Fig. 1 plots the mean of each singular value of the matrices across all the k subjects $D_1, D_2, \ldots, D_k$ and the percent of the cumulative energy of the singular values averaged across $D_1, D_2, \ldots, D_k$. It can be observed that the singular values of the matrices decay rapidly and most of the energy is concentrated in the first few components. This suggests that (1) can deal with for the iris image samples, as it does for face images. Thus, the iris recognition problem can be treated as seeking a sparse representation of the test iris in terms of the training iris images, just as the method of SRC for face recognition. Let the dictionary $D = [D_1|D_2|\cdots|D_n] \in R^{k\times m}$ be a matrix formed by concatenating the entire training set from all k classes, then, any test image y can be linearly represented by the dictionary

$$y = Dx \quad (2)$$

where x is a coefficient vector. Since y lies in the subspace spanned by the training samples of the same class as y, the vector x is sparse and only the entries associated with the class of y are nonzero, i.e. $x = [0, \ldots, 0, x_{i,1}, x_{i,2} \ldots, x_{i,n}, 0, \ldots, 0]^T$ if y is a sample of the ith class object. The special sparse structure of the coefficient vector is highly recognizable. Ideally, it identifies the label of the sample directly. However, in practical scenarios, the test samples are often partially corrupted or occluded. In this case, the low-dimensional linear model is break, and then the model formulated in (2) should be modified to an error correction version [11]

$$y = Dx + e \quad (3)$$

where $e \in R^m$ is a vector of errors, namely, an error correction term for the low-dimensional linear model.

For robust recognition task, sufficiently large size of training samples makes $n \times k > m$. Thus, the system of the linear equation (3) is typically underdetermined, and so, has no unique solution. Since under ideal condition, the test sample can be well represented by training samples from the same class as it, the solution of x is sparse enough if the number of the object classes is sufficiently large. It is reasonable to seek the sparsest solution of x for (3). Furthermore, for iris images, eyelash occlusions, eyelid overlapping, specularities and cast reflection are the most common kind corruptions of images which characterize to be large-magnitude, sparse and spatially localized, as shown in Fig. 2. That is, the vector of errors e is sparse and the values of its non-zero items are large-magnitude. Based on these observations, the sparse error correction (SEC) model instead of the standard sparse

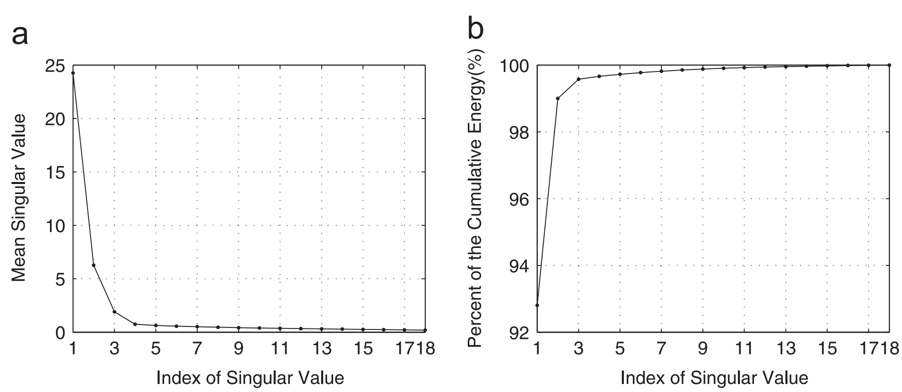

Fig. 1. The distribution of the singular values and their energy in the matrix of the iris images. (a) Means of each singular value across all classes and (b) percent of the cumulative energy of singular values.