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Occlusion invariant face recognition using selective local non-negative matrix factorization basis images

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ABSTRACT

In this paper, we propose a novel occlusion invariant face recognition algorithm based on Selective Local Non-negative Matrix Factorization (S-LNMF) technique. The proposed algorithm is composed of two phases; the occlusion detection phase and the selective LNMF-based recognition phase. We use a local approach to effectively detect partial occlusions in an input face image. A face image is first divided into a finite number of disjointed local patches, and then each patch is represented by PCA (Principal Component Analysis), obtained by corresponding occlusion-free patches of training images. And the 1-NN threshold classifier is used for occlusion detection for each patch in the corresponding PCA space. In the recognition phase, by employing the LNMF-based face representation, we exclusively use the LNMF bases of occlusion-free image patches for face recognition. Euclidean nearest neighbor rule is applied for the matching.

We have performed experiments on AR face database that includes many occluded face images by sunglasses and scarves. The experimental results demonstrate that the proposed local patch-based occlusion detection technique works well and the S-LNMF method shows superior performance to other conventional approaches.

1. Introduction

One of the most important goals of computer vision is to achieve visual recognition ability comparable to that of human [1–3]. And among many recognition subjects, the face recognition problem has been researched intensively during last few decades, due to its great potential to various practical applications such as HCI (Human Computer Interface), intelligent robot, surveillance, etc.

And, as the face recognition is studied further, obvious problem of occlusion by other objects or apparels such as sunglasses or scarves becomes eminent. Occluded parts in the face images usually degrade the recognition performance, and thus a robust algorithm for occluded faces is indispensable to real applications.

So far, several approaches that deal with occlusion have been proposed in the literature. Leonardis and Bischof [4,5] proposed a robust PCA approach that could estimate the coefficients of eigenimages from partially degraded images. Instead of computing the coefficients by projecting the data onto the eigenimages, they extracted coefficients by a robust hypothesize-and-test paradigm using subsets of image points. This approach presented successful reconstruction of partially occluded images, however the performance usually depends on the training set.

Li et al. proposed a novel method, called local non-negative matrix factorization (LNMF) [6], for learning spatially localized, parts-based subspace representation of visual patterns. In addition to the non-negativity constraint in the original NMF [7], they imposed localization constraints to the objective function. The advantages of LNMF for occluded face recognition have been demonstrated experimentally compared with the NMF and PCA methods.

Martinez [8] described a probabilistic approach that is able to compensate for imprecisely localized, partially occluded, and expression-variant faces when only single training sample per class was available to the system. To resolve the occlusion problem, each face was divided into k local regions and was analyzed separately. In contrast with other approaches where a simple voting space is used, Martinez presented a probabilistic method that analyzed how good a local match was. He demonstrated experimentally that the suppression of 1/6 of the face does not decrease accuracy. Even for those cases where 1/3 of the face is occluded, the identification results were close to those obtained in the occlusion-free case.

Recently, Tarres et al. [9] proposed a face recognition method that deals with partial occlusion by utilizing multiple PCA spaces of specific types of occluded faces using masking. But this simple approach can not cope with wide variation of occlusion types

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robustly, and also it requires large memory and longer processing time.

In this paper, we present a novel face recognition algorithm robust to occlusion using S-LNMF technique. The proposed algorithm is based on a local approach where face images are divided into a finite number of disjointed local patches. But, unlike previous approaches, we perform occlusion detection explicitly. The occluded regions in the face images are detected by the 1-NN classifier. And then, the recognition process is performed using the selected LNMF bases that correspond to the occlusion-free patches. We evaluate our algorithm on the occlusion subset as well as the expression and lighting subsets of the AR database [10], and demonstrate that the proposed algorithm produces superior performance to previous face recognition schemes.

The remainder of this paper is organized as follows. In Section 2, we introduce a local approach and deriving classifiers for occlusion detection. In Section 3 we describe how the S-LNMF bases images can be used for occluded face recognition. After presenting our experimental results in Section 4, we conclude in Section 5.

2. Occlusion detection

The proposed face recognition algorithm is based on selected LNMF subspace matching. Note that since each LNMF basis image exhibits high localization characteristics in spatial domain, local occlusion affects only the coefficients of the corresponding bases, so that the error becomes not global but local. So, by using the LNMF bases for occlusion-free regions exclusively, we can achieve robust matching for occlusion. However, to select relevant local bases, we need to determine which parts are occluded in a face image in advance. Since this occlusion detection step usually influences the overall performance of the face recognition system, it must be carefully designed. In this section we propose an efficient occlusion detection algorithm based on one class classifier in the PCA (Principal Component Analysis) space.

2.1. Local subdivision of a face image

Partial occlusions in face images usually occur when subjects wear adornments like sunglass or scarf, or when faces are covered by other objects such as hand, cup and so on, as shown in Fig. 1. To detect the locally occluded regions in a face image, we first divide the image into a finite number of local disjoint patches [8], and then examine each patch individually. In general, the configuration and the sizes of patches are important factors in overall recognition performance. In this paper, the optimal division of face images was obtained empirically; we employ a division of a face image into symmetric 6 local patches as in Fig. 2.

2.2. Local occlusion detection in PCA subspace

Occlusion detection of a given face image is accomplished for each local patch independently by employing a pattern classification framework. Note that each local patch is still a high dimensional vector that is computationally infeasible. So we deal with each patch image in a low dimensional subspace after the dimension reduction using PCA [11–16].

(a) normal (b) sunglass (c) scarf

Fig. 1. Examples of occluded face images.

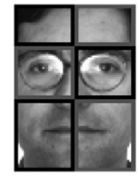

Fig. 2. Local subdivision of a face.

(a) sunglass (b) scarf

Fig. 3. Local approaches on occluded face images.

Six PCA subspaces corresponding to the 6 local patches of occlusion-free faces are trained by normal face images. PCA coefficients of each patch of the training images are calculated by

$$\Omega_{i,k} = E_k^T(X_{i,k} - \Psi_k), \quad i = 1, 2, \dots N, \ \ k = 1, 2, \dots 6, \tag{1}$$

where $X_{i,k}$ is the k_{th} patch of the i_{th} image, Ψ_k is the average image of k_{th} patch, E_k is the eigenmatrix of the k_{th} patch, and N is the total number of training images.

When a test face image is given, it is divided into 6 local patches as shown in Fig. 3, and then the patches, $\Gamma_k k = 1,2,\dots 6$, are projected onto the corresponding eigenspace E_k, producing corresponding coefficients vectors

$$\gamma_k = E_k^T(\Gamma_k - \Psi_k), \quad k = 1, 2, \dots, 6. \tag{2}$$

So, the occlusion detection for each patch is accomplished by comparing the coefficient vectors of occlusion-free images with that of the test image in the corresponding eigenspace.

2.3. One class classifiers

To distinguish normal data from occluded ones in eigenspace, we need a proper classifier. Occlusion detection problem can be thought as the one class classification problem [17,18]. Fig. 4 shows an example of one-class classification problem in feature space, where the dots represent the occlusion-free patches to be

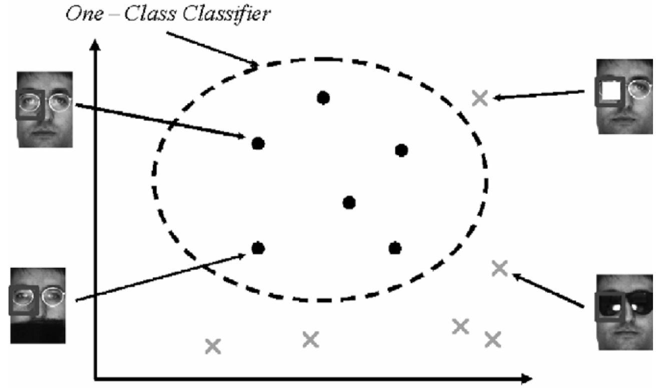

Fig. 4. One-Class Classifier.