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Robust low-resolution face recognition via low-rank representation and locality-constrained regression☆

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A B S T R A C T

Recognizing face images in low-resolution (LR) scenarios have bigger challenges than recognizing those in high-resolution (HR) scenarios due to that LR images usually lack discriminative details. Previous methods ignore the existence of occlusions in the LR probe images. To alleviate this problem, we propose a low-rank representation and locality-constrained regression (LLRLCR) based method in this paper to learn occlusion-robust representations features for final face recognition tasks. For HR gallery set, LLRLCR uses double low-rank representation to reveal the underlying holistic data structures; for LR probe, LLRLCR uses locality-constrained matrix regression to keep regression error's structural information and to learn robust and discriminative representation features. The proposed method allows us to fully exploit the structure information in gallery and probe data simultaneously. Finally, after getting the occlusion-robust features, the face labels can be predicted via a simple yet powerful sparse representation based classifier engine. Experiments on some standard face databases have indicated that the proposed method can obtain promising recognition performance than some state-of-the-art LR face recognition approaches.

1. Introduction

Because of the wide range of applications (e.g., access control, identity authentication and security monitoring), face recognition (FR) has attracted considerable attention in past two decades [1-6]. However, in many real-world applications, due to the long distance between the subject and camera, the acquired face images usually have low-resolution (LR), making face recognition almost impossible. This refers to low-resolution face recognition (LR FR) problem [7]. Generally, there are three strategies to match a LR probe image with a high-resolution (HR) gallery one (as shown in Fig. 1): (i) match the

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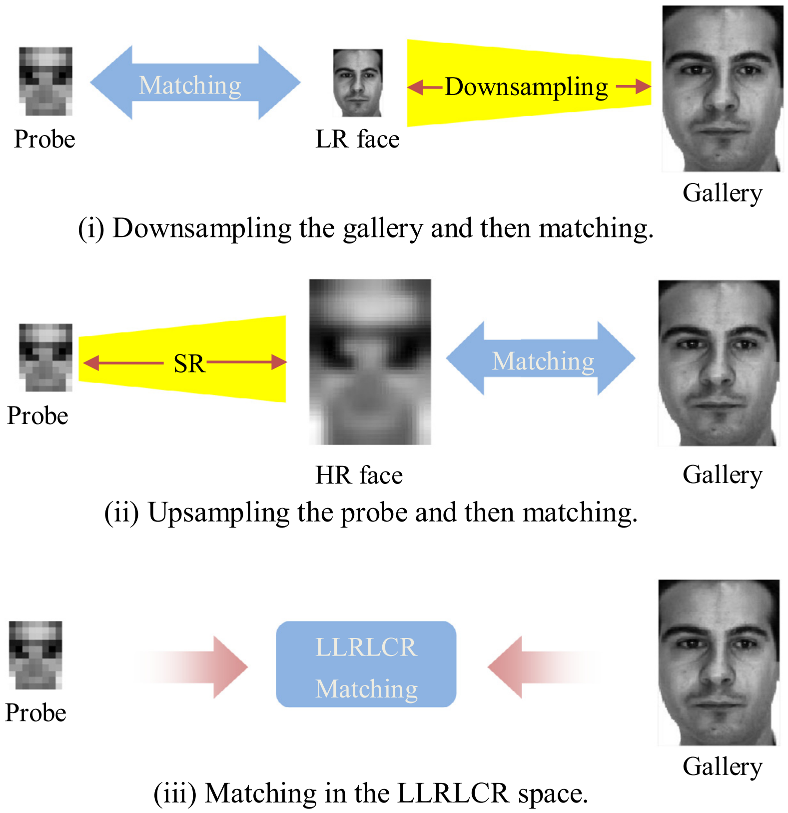

Fig. 1. Standard approaches to match an input LR probe to a HR gallery. (i) Match the down-sampled HR gallery with the LR probe; (ii) match HR gallery with the up-sampled LR probe; (iii) matching in the common space. The proposed method belongs to the third king of approach.

down-sampled HR gallery with the LR probe; (ii) match HR gallery with the up-sampled LR probe; (iii) map both the LR probe and the HR gallery into a common space and then implement matching.

1.1. Prior work

Super-resolution (SR) [8,9] technologies have been widely employed to enhance images resolution. Due to the super-resolution performance even with large magnification factor, learning-based SR approaches have obtained more considerations than interpolation-based ones. As we all known that Baker et al. [10] firstly proposed a face hallucination technology, which infers the HR image with the assistance of HR-LR training dictionary pairs under the Bayesian formulation. Wang et al. [11] coded the LR probe as a linear combination over the LR training dictionary with the help of eigentransformation technology. Huang et al. [12] applied canonical correlation analysis (CCA) to find a coherent subspace which maximizes the correlation between the principal component analysis (PCA) coefficients of corresponding LR and HR images. Recently, many literatures conclude that patch based methods can obtain better performance than global based ones. Following the well-known neighbor embedding (NE) method, Chen et al. [13] presented a low-rank variant based super-resolution method. Then, many researchers state that the position information is useful for face hallucination. Ma et al. [14] designed a position-patch based face hallucination model using all patches from the same position in a training dictionary. To deal with the over-fitting problem in [14], Jung et al. [15] and Jiang et al. [16] employed locality and sparsity prior to improve the super-resolution reconstruction results with only several principal training patches. Most recently, Jiang et al. [17] further presented a multilayer neighbor embedding scheme for efficient face hallucination.

These above mentioned super-resolution approaches aim at achieving good reconstructed image quality, they ignore the discriminative features, which are vital for the following face recognition process. Many resolution robust feature based methods have been proposed to enhance the discriminative ability on the common feature space. Hennings–Yeomans et al. [18] proposed to include the extracted face features in a SR method to simultaneously provide measures of fit of the results from both recognition and reconstruction perspectives. Huang et al. [19] built a nonlinear mapping between LR and HR features by radial basis functions with lower regression errors in a coherent feature space. Biswas et al. [20] proposed to use multidimensional scaling to transform the features of LR probe image and the HR gallery image into a distance-preserving feature space. Jiang et al. [21] developed a method based on coupled discriminant multi-manifold analysis (CDMMA) which learnt mapping simultaneously from the neighboring information as well as the local geometric structure implied by the