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An ensemble of patch-based subspaces for makeup-robust face recognition

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ABSTRACT

Recent research has demonstrated the negative impact of makeup on automated face recognition. In this work, we introduce a patch-based *ensemble* learning method, which uses multiple subspaces generated by sampling patches from before-makeup and after-makeup face images, to address this problem. In the proposed scheme, each face image is tessellated into patches and each patch is represented by a set of feature descriptors, viz., Local Gradient Gabor Pattern (LGGP), Histogram of Gabor Ordinal Ratio Measures (HGORM) and Densely Sampled Local Binary Pattern (DS-LBP). Then, an improved Random Subspace Linear Discriminant Analysis (SRS-LDA) method is used to perform ensemble learning by sampling patches and constructing multiple common subspaces between before-makeup and after-makeup facial images. Finally, Collaborative-based and Sparse-based Representation Classifiers are used to compare feature vectors in this subspace and the resulting scores are combined via the sum-rule. The proposed face matching algorithm is evaluated on the YMU makeup dataset and is shown to achieve very good results. It outperforms other methods designed specifically for the makeup problem.

1. Introduction

Automated face recognition has been adopted in a broad range of applications such as personal authentication, video surveillance, image tagging, and human–computer interaction [1]. Automated face recognition systems recognize an individual by extracting a discriminative set of features from an input face image and comparing this feature set with a template stored in a database [1]. The recognition accuracy of these systems has rapidly improved over the past decade primarily due to the development of robust feature representations and matching techniques [2–5], as evidenced by significant reduction in error rates on several public benchmark databases (e.g., FRGC [6], LFW [7], YTF [8]). However, a number of challenges still remain particularly in *Heterogeneous Face Recognition* where the images to be matched are fundamentally different, e.g., visible versus thermal face images or face sketches versus photographs.

More recent research has investigated the problem of matching faces that have been altered either by plastic surgery [9] or by the application of facial cosmetics (i.e., makeup). In this work, we focus on the problem of matching face images before and after the application of makeup. These images are not acquired in a controlled environment, and hence considered as makeup in the wild. This problem is especially significant since makeup is a commonly used modifier of facial appearance. Thus, researchers in biometrics and cognitive psychology [10] are interested in understanding the effect of this modifier on face recognition.

1.1. Makeup challenge

Recent studies have demonstrated that makeup can significantly degrade face matching accuracy [11–13]. Makeup is typically used to enhance or alter the appearance of an individual's face. It has become a daily necessity for many, as reported in a recent British survey,[1] and as evidenced by a sale volume of 3.6 Billion in 2011 in the United States.[2] The cosmetic industry has developed a number of products, which can be broadly categorized as skin, eye or lip makeup. Skin makeup is utilized to alter skin color and texture, suppress wrinkles, and cover blemishes and aging spots. Lip makeup is commonly used to accentuate the lips (by altering contrast and the perceived shape) and to restore moisture. Eye makeup is widely used to increase the contrast in the periocular region, change the shape of the eyes, and

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[1] http://www.superdrug.com/content/ebiz/superdrug/stry/cgq1300799243/surveyrelease-jp.pdf.
[2] https://www.npd.com/wps/portal/npd/us/news/press-releases/pr_120301/.

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1566-2535/

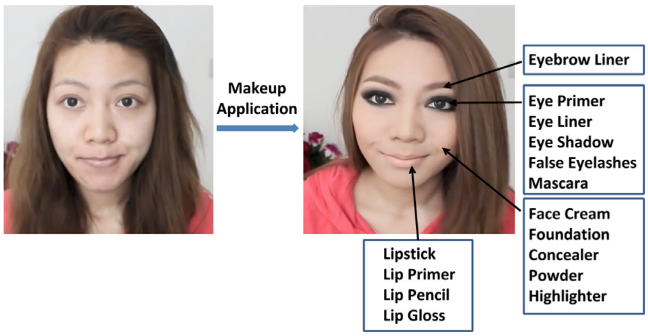

Fig. 1. An example showing how makeup can easily change the overall facial appearance, resulting in possible false non-match errors. Images are obtained from Youtube.

accentuate the eye-brows [14]. An example demonstrating the impact of applying makeup can be seen in Fig. 1.

Makeup poses a *challenge to automated face recognition* due to its potential to substantially alter the facial appearance. For example, it changes the perceived facial shape and appearance, modifies contrast levels in the mouth and eye region, and alters skin texture (see Fig. 1). Such modifications can lead to large intraclass variations, resulting in false non-matches, where a subject's face is not successfully recognized. Recent work by Dantcheva et al. [11] suggested that the recognition accuracy of both commercial and academic face recognition methods can be reduced by upto 76.21% due to the application of makeup.[3] It was concluded that non-permanent facial cosmetics can dramatically change facial appearance, both locally and globally, by altering color, contrast and texture. Existing face matchers, which rely on the cues of contrast and texture information for establishing a match, can be impacted by the application of facial makeup. It was also observed that the impact due to the application of eye makeup is considered to be more pronounced than lipstick makeup in our previous work [11]. The combination of eye and lipstick makeups poses a greater challenge than individual ones. Solutions to address this challenge are important towards developing robust face recognition systems.

1.2. Motivation and related work

To date, there is limited scientific literature on addressing the challenge of make-up induced changes. Chen et al. [15] presented an automated *makeup detection* approach, that was used to adaptively modify images prior to performing face recognition. Hu et al. [16] used canonical correlation analysis (CCA) along with a support vector machine (SVM) classifier to facilitate the matching of before-makeup and after-makeup images. Guo et al. [12] learned the mapping between features extracted from patches in the before- and after-makeup images in order to minimize the disparity between the images to be matched. The mapping was learned using CCA, rCCA (regularized CCA) and Partial Least Squares (PLS) methods. While *mapping-based methods* have been shown to be effective, they have two main limitations. First, the mapping between before-makeup and after-makeup facial images can be complex, spatially variant and nonlinear. Therefore, it is insufficient to learn a single mapping in order to describe the complex relationship between before-makeup and after-makeup samples [17]. Second, CCA and PLS methods have a tendency to overfit the training data and thus do not generalize well on unseen subjects [18].

In order to overcome these problems, we propose to use an *ensemble learning scheme [19,20] to generate multiple common semi-random subspaces for before-makeup and after-makeup samples*, instead of two separate subspaces. In random subspace methods, a set of multiple low-dimensional subspaces are generated by randomly sampling feature vectors in the original high-dimensional space [21]. It has proven to be effective in various tasks of face recognition [21–24]. For instance, Wang and Tang [21] proposed the use of Random Subspace Linear Discriminant Analysis (RS-LDA) for face recognition by randomly sampling eigenfaces. Zhu et al. [22] randomly sampled features on local image regions to construct a set of base classifiers. RS-LDA method [23,24] was also adapted for matching near-infrared images against visible images. The motivation for using a random subspace method are as follows [25]: (a) a learning algorithm can be viewed as searching for the best classifier in a space populated by different weak classifiers; (b) many weak classifiers are considered to be equally favorable when given a finite amount of training data; (c) averaging these individual classifiers can better approximate the true classifier. Therefore, a random subspace method can be used to generate multiple common subspaces, where each subspace contains a small portion of discriminative information pertaining to the identity. At the same time, by randomly selecting different patches as the input to each subspace-based classifier, the overfitting issue is avoided [21].

2. Proposed method

In this work, a patch-based ensemble learning scheme for face recognition in the presence of makeup is proposed (see Fig. 2). Given a face image, the proposed method first tessellates the image into patches and then applies multiple feature descriptors to each patch based on Local Gradient Gabor Pattern (LGGP) [26], Histogram of Gabor Ordinal Ratio Measures (HGORM) and Densely Sampled Local Binary Pattern (DS-LBP). These descriptors capture both global (LGGP and HGORM) and local (DS-LBP) information. Next, a weight learning scheme based on Fisher's separation criteria [27] is utilized to rank the significance of each patch. Then, a semi-random sampling method, based on the weights associated with the patches, is used to select multiple sets of patches and construct subspaces. This process is repeated for each of the three descriptors. Finally, Collaborative-based Representation Classifiers (CRC) and Sparse-based Representation Classifiers (SRC) are utilized in these subspaces resulting in an ensemble of classifiers for each descriptor. The scores generated by the classifiers are then fused using the sum-rule, which takes the weighted average of scores from multiple modalities [28]. The proposed method involves two levels of information fusion: the fusion of subspace classifiers corresponding to individual descriptors, and the fusion of matching scores generated by all descriptors. The rationale for the proposed method are as follows: (1) a single descriptor is not sufficient enough to describe a face image; (2) the prior knowledge about which patch is impacted by makeup is unknown; (3) semi-random sampling can increase the probability of selecting patches that are not impacted by makeup. The proposed framework is illustrated in Fig. 2. As can be seen from this figure, the sum-rule is used for first fusing the scores corresponding to the multiple subspaces and then the scores corresponding to the three descriptors.

Our approach to match two face images of the same person, acquired before and after the application of makeup, differs from previously published works with RS-LDA [21–24]. In the work of [21] and [22], the RS-LDA method was not used to handle heterogeneous face recognition. In [23] and [24], the patch sampling procedure is performed *across* different feature descriptors (SIFT and LBP), while our patch sampling is performed *within* the same feature descriptor.

Contributions:

1. We propose an ensemble framework for a face matcher that is robust to the application of makeup. The approach utilizes multiple subspaces corresponding to three different feature descriptors

[3] http://www.antitza.com/makeup-datasets-benchmark.html.