Face Authentication With Makeup Changes

Guodong Guo, *Senior Member, IEEE,* Lingyun Wen, and Shuicheng Yan, *Senior Member, IEEE*

***Abstract*—Recent studies have shown that facial cosmetics have an impact on face recognition. To develop a face recognition system that is robust to facial makeup, we propose performing correlation mapping between makeup and nonmakeup faces on features extracted from local patches. Three methods are explored to learn the correlations. We also study the problem of makeup detection. Four categories of features are proposed to characterize cosmetics, including skin color tone, skin smoothness, texture, and highlight. A patch selection scheme and discriminative mapping are presented to enhance the performance of makeup detection. A complete system is then developed for face verification utilizing the makeup detection result. Experimental results show that our system is robust to cosmetics in face authentication. An accuracy of about 80.0% can be achieved on a database of about 500 pairs of makeup and nonmakeup face images.**

***Index Terms*—Correlation, cosmetics, discriminative, face verification, makeup detection, partial least squares, patch selection.**

I. Introduction

HUMAN FACE recognition is important for many real applications. Researchers have worked for decades to make the recognition more robust and have high performance. In recent human perception and psychology studies [17], [27], it has been revealed that heavy makeup can significantly decrease the human ability to recognize faces. In a very recent computational study, the impact of facial makeup on face recognition has been presented [7]. Existing face matching methods based on contrast and texture information can be impacted by the application of facial makeup.

In reality, however, it is quite common for women to wear cosmetics to hide facial flaws and to appear more attractive. Archaeological evidence of cosmetics dates back to at least ancient Egypt and Greece [2], [4]. The improved attractiveness using cosmetics has been studied in [8] and [10]. Facial cosmetics or makeup can change the perceived appearance of faces [7], [17], [27]. As shown in Fig. 1, significant appearance changes can be observed for individuals with and without makeup.

Manuscript received March 1, 2013; revised June 12, 2013 and July 29, 2013; accepted August 12, 2013. Date of publication September 27, 2013; date of current version May 2, 2014. This work was supported in part by grants from the Center of Identification Technology Research and the Singapore National Research Foundation under its International Research Centre at Singapore Funding Initiative and was administered by the IDM Program Office. This paper was recommended by Associate Editor G. Doerr.

G. Guo and L. Wen are with the Lane Department of Computer Science and Electrical Engineering, West Virginia University, Morgantown, WV 26506 USA (e-mail: guodong.guo@mail.wvu.edu; lwen@mix.wvu.edu).

S. Yan is with the Department of Electrical and Computer Engineering, National University of Singapore, Singapore (e-mail: eleyans@nus.edu.sg).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TCSVT.2013.2280076

Fig. 1. Pairs of face images of the same individuals in makeup (columns 1 and 3) or nonmakeup classes (columns 2 and 4), showing significant appearance changes. We study how to perform face authentication that is robust to makeup changes.

In order to develop a robust system for face recognition, the influence caused by cosmetics needs to be addressed. A dual-attributes approach [30] was proposed to learn facial attributes in makeup and nonmakeup faces separately, and face matching uses the semantic-level attributes to reduce the influence of makeup on low-level features. Another approach [5] is to preprocess face images with a self-quotient image technique to reduce makeup effects before face matching. However, these methods cannot reduce the makeup influence significantly.

In this paper, we propose to explore a correlation-based scheme for makeup-invariant face authentication. The underlying assumption is that the pair of face images of the same person should have the maximum correlation no matter how the appearance changes with the presented cosmetics, while different persons should not have a large correlation even if they have the same makeup or are not wearing any makeup. The main idea is that a relationship will be built for a pair of face images of the same person although the makeup is different, e.g., with or without. Based on the learned correlation bases, the makeup and nonmakeup faces will be projected to respectively, the faces of the same person will have more similar features in the transformed feature space. The transform is based on the projection on the learned bases. The basic framework of our proposed approach can be illustrated in Fig. 2.

We also study the makeup detection problem. There are some recent works related to this problem. The appearance of cosmetic foundation on face images was studied using a

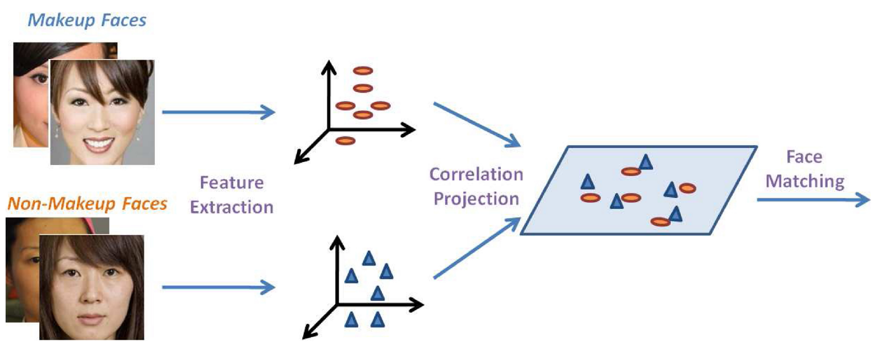


Fig. 2. Basic framework that we propose for face recognition that is robust to cosmetic changes based on a correlation mapping.

multiband camera system and the oily-shine regions in makeup face images were detected using a clustering method [16]. There is no result on the classification of makeup and nonmakeup faces in [16]. A system was developed in [29] to detect eye-shadow, lipstick, and liquid foundation, separately, in makeup faces of only 21 subjects. Both the HSV color space and texture features were used. However, there is no classification between makeup and nonmakeup faces in [29]. Motivated by [29], Chen *et al.* [5] explored the binary classification of makeup and nonmakeup faces, using the shape, texture, and color features. While work in [5] is close to ours, there are significant differences. We consider more makeup cues and use 12 facial patches (only three patches were used in [5]). There is neither patch selection nor discriminative mapping in [5], whereas those steps are essential to obtain a high accuracy for makeup detection, as shown in our experiments. Finally, our makeup detection experiments are conducted on a much larger database of 500 subjects, while only 125 subjects were used in [5].

Based on how humans apply cosmetics, we present four categories of features to characterize the facial makeup. Different schemes, e.g., patch selection and discriminative mapping, are applied to improve the makeup detection performance. Using the makeup detection result, we can develop a complete system for face verification, in which the correlation bases can be selected automatically without user interaction.

Our major contributions include the following.

1) We propose a method for face authentication that is robust to cosmetic changes, based on the correlation of local features between makeup and nonmakeup faces.
2) We develop a method to detect facial makeup, which is useful itself for facial analysis, and can help develop a complete system for face authentication with an automated correlation bases selection.

In the remaining, we introduce the correlation-based approaches to robust face verification in Section II. Then, the makeup detection problem is studied in Section III, which can help to make it automatic for our face verification with makeup changes. The experiments are conducted in Section IV and, finally, some concluding remarks are given.

II. Robust Face Verification

To develop a robust face recognizer that is insensitive to facial makeup changes, we propose to use a correlation-based scheme. To learn the correlation between makeup and nonmakeup face images, we explore three methods, partial least squares (PLS), canonical correlation analysis (CCA), and the regularized CCA (rCCA). We investigate if these methods are useful for face recognition invariant to facial cosmetics, and how different the performance will be among these methods. In the following, we introduce these methods briefly.

A. Partial Least Squares

Partial least squares (PLS) models relationships between sets of observed variables by means of latent variables [18], [19], [32]. PLS methods rely on the assumption that the observed data is generated by a system that contains a small number of latent variables [19]. It has been shown to be a powerful technique when observed variables are highly correlated [18].

Suppose we have two data sets $\mathbf{X}$ and $\mathbf{Y}$, containing n data samples each, where $\mathbf{X} \subset \mathbf{R}^N$ and $\mathbf{Y} \subset \mathbf{R}^M$, and $\mathbf{R}^N$ and $\mathbf{R}^M$, stand for N-dimensional and M-dimensional spaces, respectively. PLS models the relations between $\mathbf{X}$ and $\mathbf{Y}$ by means of score vectors such that

$$\begin{aligned} \mathbf{X} &= \mathbf{TP}^T + \mathbf{E} \\ \mathbf{Y} &= \mathbf{UQ}^T + \mathbf{F} \end{aligned} \tag{1}$$

where $\mathbf{T}$ and $\mathbf{U}$ are extracted score vectors (latent vectors), the $\mathbf{P}$ and $\mathbf{Q}$ represent matrices of loadings, and the $\mathbf{E}$ and $\mathbf{F}$ are the matrices of residuals [18].

The PLS usually uses a greedy strategy to find multiple basis vectors that project $\mathbf{X}$ and $\mathbf{Y}$ to a latent space. Its classical form is based on the nonlinear iterative partial least squares (NIPALS) algorithm [31] to find weight vectors $\mathbf{w}$, $\mathbf{c}$ to satisfy

$$\begin{aligned} [cov(\mathbf{t}, \mathbf{u})]^2 &= [cov(\mathbf{Xw}, \mathbf{Yc})]^2 \\ &= max_{|r|=|s|=1} \, [cov(\mathbf{Xr}, \mathbf{Ys})]^2 \end{aligned} \tag{2}$$

where $cov(\mathbf{t}, \mathbf{u}) = \frac{\mathbf{t}^T\mathbf{u}}{n}$ denotes the sample covariance between the score vectors $\mathbf{t}$ and $\mathbf{u}$ [18]. The linear PLS models can have variants based on the deflation difference [19].

The PLS models were originally derived for regression or classification problems [19], [31], [32]. Here, we explore the PLS method for a new problem, called face verification under cosmetic changes, where both $\mathbf{X}$ and $\mathbf{Y}$ are face images but in different groups (makeup or nonmakeup).

B. Canonical Correlation Analysis

Canonical correction analysis (CCA) is introduced by Hotelling [13] to describe the linear relation between two multidimensional variables as the problem of finding basis vectors for each set such that the projections of the two variables on their respective basis vectors are maximally correlated [12].

Let p-dimensional x and q-dimensional y denote the two sets of real-valued zero-mean random variables (i.e., $x \in R^p$ and $y \in R^q$). Let the $p \times N$ matrix X be the data matrix of the first set, and the $q \times N$ matrix Y be the data matrix of the second set. The CCA method computes two projection vectors, $w_x \in R^p$ and $w_y \in R^q$, such that the correlation coefficient

$$\rho = \frac{w_x^T XY^T w_y}{\sqrt{(w_x^T XX^T w_x)(w_y^T YY^T w_y)}} \quad (3)$$

is maximized [12], [13]. Since ρ is invariant to the scaling of w_x and w_y, CCA can be formulated equivalently as

$$\max_{w_x, w_y} w_x^T XY^T w_y \quad (4)$$

subject to $w_x^T XX^T w_x = 1$ and $w_y^T YY^T w_y = 1$.

It can be shown [12] that w_x can be obtained by solving the following generalized eigenvalue problem:

$$XY^T(YY^T)^{-1}YX^T w_x = \lambda XX^T w_x \quad (5)$$

where λ is the eigenvalue corresponding to the eigenvector w_x. It has also been shown [12] that multiple projection vectors under certain orthonormality constraints consist of the top l eigenvectors of the generalized eigenvalue problem in (5).

The CCA methods have been applied to solve some computer vision problems, e.g., image annotation [11], action classification [14], and face recognition [15], [23]. Here, we exploit the CCA method for face analysis with makeup changes.

C. Regularized CCA

In regularized CCA or rCCA, a regularization term is added to each data set to stabilize the solution [24]. The corresponding generalized eigenvalue problem is given by

$$\begin{aligned} &XY^T[(1-\gamma_y)YY^T + \gamma_y I]^{-1}YX^T w_x \\ &\quad = \lambda[(1-\gamma_x)XX^T + \gamma_x I]w_x. \end{aligned} \quad (6)$$

When $\gamma_x = \gamma_y = 0$, the rCCA becomes the standard CCA. Usually, γ_x and γ_y can take values between 0 and 1. In our study, we found that the performance of the rCCA is not sensitive to the values of γ_x and γ_y. We simply set $\gamma_x = \gamma_y = 0.09$ for all our experiments. In applying the CCA technique for computer vision problems, usually the standard CCA is adopted [23]. In our problem, we explore if the rCCA can have some improvement over the standard CCA, and also compare it to the PLS method.

D. Correlation on Facial Features

The correlation methods introduced above will be applied to the extracted features in face images, rather than raw pixel values, because facial makeup may change the facial appearance significantly in terms of single pixel values, and the changes of pixel values may be different for different facial parts and different individuals. Building the correlations on extracted features rather than raw pixel values may relieve the problem of pixel value changes caused by facial makeup to some degree.

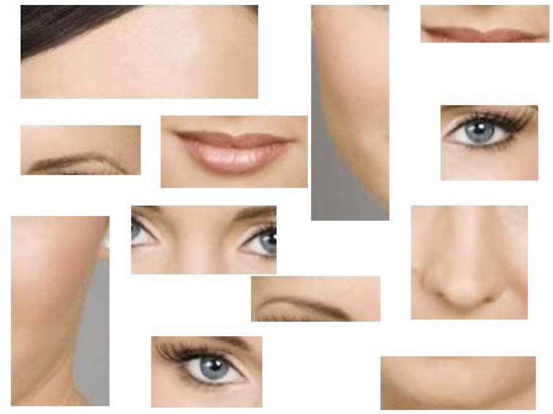


Fig. 3. Facial patches used in our experiments. There are 12 local patches selected for each face image to perform local patch-based facial analysis.

In extracting facial features, we use some standard methods for facial feature representation, such as the local binary patterns (LBP) [3] and the histogram of oriented gradient (HOG) [6]. The principal component analysis (PCA) is usually used for dimensionality reduction; it can compute the eigenfaces [26] for facial feature characterization. The projection coefficients are used as features for face representation in Eigenfaces [26], which are used frequently in face recognition. So we also investigate the eigenfaces representation (called PCA) in our correlation analysis. Our emphasis is that the correlations need to be performed on those features rather than on raw pixels directly.

In some previous approaches [20], [23], the PLS or CCA correlation is applied to raw face images. We found that the performance will deteriorate when the correlation methods are applied to raw images, which can be demonstrated in our experiments. This fact tells that our problem of face authentication with facial makeup changes has some special properties itself and is different from the problems studied in [20], [22], and [23]. In addition, our problem might be more challenging than those in [20] and [23], since the direct correlation on raw pixels values has a significantly lower accuracy in our problem. Finally, we use local patches rather than the whole face image, which is essential for our problem, and will be presented next.

E. Local Patches

In addition to learning correlations on extracted features rather than raw pixels, we also found that local patches have to be used in computing the correlations and extracting features. This can be demonstrated in our experiments because different facial regions could be applied with different cosmetic products and with different amounts or degrees. For example, the eye makeup may use various colors (e.g., gold soft smoky, bronze) to make the eye look youthful and the lashes extra-long, while red or other coloration may be applied to the mouth to reshape (e.g., reduce, increase, or bring balance to the lips) to have a beautiful look. It might be difficult to learn a correlation of global faces between makeup and nonmakeup. To deal with this problem, we use local patches on face images. Another advantage of using local patches is that the local patches can also make our approach robust to head pose changes, facial expressions, or illumination variations, in addition to cosmetic changes. As a result, both the feature extraction and correlation learning are based on local patches, rather than a global face image. Again, this is different from the use of whole images in [20] and [23]. The patches we use in each face image are illustrated in Fig. 3.

III. Facial Makeup Detection

We study the facial makeup detection problem. It is to classify a face image into the makeup or nonmakeup class. The makeup detection result can help our face authentication with makeup changes, providing the automated selection of bases for feature projection. Based on how humans apply cosmetics [1], we will develop different cues to characterize facial makeup computationally. Then, we propose to perform patch selection and discriminative mapping to enhance the performance of makeup detection.

A. Characterization of Facial Makeup

We propose four different methods to characterize facial makeup based on knowledge of cosmetics [1].

1) *Skin Color Tone:* The facial skin color tone may be changed after applying cosmetic products on a face. The changed skin color tone may make a person look beautiful and younger [1]. Thus, it is intuitive that the facial skin color tone can be used to characterize facial makeup. In other words, faces with and without makeup can be separated based on measuring the skin color difference.

We compute the mean, standard deviation, and entropy, denoted by μ, σ, and E, respectively, to characterize the skin color tone in each of the three color channels (R, G, and B) for each facial patch. As a result, nine features are extracted for each image patch in a face image.

Suppose the normalized histogram of the pixel values in each patch is denoted by $H(i)$, where i is the index of the pixel values. The number of pixels within the patch is N. Then, the mean, standard deviation, and entropy are computed for each image patch by

$$\mu_c = \sum_i H(i) * i \tag{7}$$

$$\sigma_c = \sqrt{\sum_i (i-\mu)^2 * H(i)} \tag{8}$$

$$E_c = -\sum_i H(i) \log_2 H(i) \tag{9}$$

in each color channel $c \in \{r, g, b\}$.

2) *Facial Skin Smoothness:* When the faces have makeup, the facial smoothness may be changed. Through applying foundation cream or other cosmetic products to faces, the facial appearance may look smoother. Thus, the measure of facial smoothness may be used to determine whether a face has makeup or not.

In characterizing the facial smoothness, only the image intensity values are used within each patch in a face image. We compute the mean, standard deviation, and entropy, respectively, using (7), (8), and (9), but in image patch intensities only.

3) *Skin Texture:* With the use of cosmetic products on faces, the facial skin texture might look different. The texture change may be coupled with smoothness changes, but we want to characterize the skin texture specifically. To characterize the skin texture patterns, we use the LBP [3], which is a simple and popular method to extract texture features. It is computed by comparing the intensity value of a center pixel with its surrounding neighbors. A small neighborhood (3×3) is used in our LBP texture feature extraction. A zero or one results for each comparison to represent the relation of larger than or less than. The binary patterns are usually encoded with eight bits and the histogram is computed for each region of interest. We compute the LBP features for each patch in a face image.

4) *Highlight:* The facial highlight may be perceived differently between faces with makeup and without. Characterizing the facial highlight might be useful to discriminate makeup faces from nonmakeup faces. The makeup foundation may change the highlight on face images [16]. To explore this, we compute facial highlight in face images and then extract related features to characterize the highlight component for facial makeup detection.

To compute the facial highlight, we adopt the dichromatic reflection model [21] to characterize the facial reflection, which is a simple linear combination of specular $\mathcal{I}^S$ and diffuse $\mathcal{I}^D$ components for the reflected light color $\mathcal{I}$ at each pixel

$$\mathcal{I} = \mathcal{I}^D + \mathcal{I}^S \tag{10}$$

where $\mathcal{I} = \{I_r, I_g, I_b\}$ is the image color with three color components. Define chromaticity or normalized color as

$$\sigma_c = \frac{I_c}{\sum_{c\in\{r,g,b\}} I_c} \tag{11}$$

where $c \in \{r, g, b\}$. Similarly, we can define diffuse chromaticity Λ_c and illumination chromaticity Γ_c by

$$\Lambda_c = \frac{I_c^D}{\sum_{c\in\{r,g,b\}} I_c^D}, \quad \Gamma_c = \frac{I_c^S}{\sum_{c\in\{r,g,b\}} I_c^S}. \tag{12}$$

The maximum chromaticity can be defined [25] by

$$\sigma_{max} = \max\{\sigma_r, \sigma_g, \sigma_b\} \tag{13}$$

and similarly for maximum diffuse chromaticity by

$$\Lambda_{max} = \max\{\Lambda_r, \Lambda_g, \Lambda_b\}. \tag{14}$$

Then, the diffuse component can be computed by

$$I_c^D(\Lambda_{max}) = I_c - \frac{\max_{c\in\{r,g,b\}} I_c - \Lambda_{max}\sum_{c\in\{r,g,b\}} I_c}{1 - 3\Lambda_{max}} \tag{15}$$

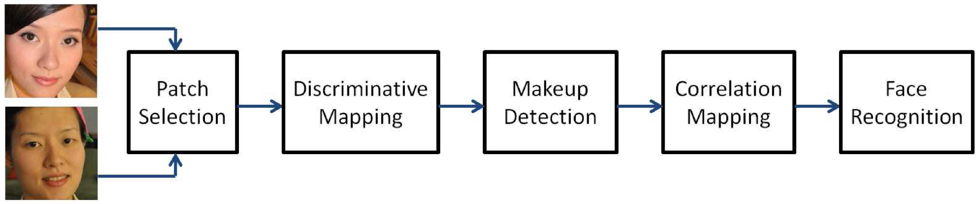


Fig. 4. Complete framework of integrated makeup detection and face verification. Given a pair of face images with extracted features, the system performs patch selection, discriminative mapping, and makeup detection. Then the correlation mapping can be executed based on the recognized makeup or nonmakeup. Finally, face verification is accomplished. The system can perform both face matching and makeup detection.

according to [25]. Therefore, the highlight detection problem can be formulated as the searching for the maximum diffuse chromaticity Λ_{max}, which changes from pixel to pixel [25] and can be improved based on bilateral filtering in Λ_{max} estimation [34]. The method of bilateral filtering-based estimation is used for highlight detection in our makeup detection problem.

Given the detected highlight, we compute the mean, standard deviation, and entropy, in each of the designated patches in the highlight image, using methods similar to (7), (8), and (9).

B. Patch Selection

In the above, we introduced four different ways to characterize facial makeup. Each feature is computed in each facial patch independently. We found that the performance will be much lower when these features are computed in the whole face image (see experiments in Section IV). The reason might be that the cosmetic products are used differently on different facial parts, and the cosmetic effect may be more significant on some parts than others. Therefore, we emphasize the use of local patches for facial makeup characterization. Furthermore, the designated facial patches might not be equally useful for facial makeup detection. To explore this, we perform patch selection using a greedy method.

Specifically, we measure the accuracy or capability of each patch for facial makeup detection. All of the patches are sorted in a descending order based on their classification accuracies. Starting from the rank-1 patch, we sequentially add patches, one by one, and measure the accuracy again when each new patch is added. It follows the similar procedure until all patches are added. Then, the peak value with the highest accuracy will be selected to obtain the proper number of patches and to determine which patches to use for facial makeup classification. This process is done for each of the four features separately. Based on this greedy search method, we can find all useful patches in each feature representation for makeup detection.

C. Discriminative Mapping

After patch selection, we obtain the useful patches for makeup classification. However, there are still two things to consider: 1) if the features on the selected patches can be integrated together and 2) if the features on the selected patches can be made more discriminative to improve the recognition accuracy. To address these, we will combine the selected patches with each corresponding feature, and use a discriminative mapping method to make the combination more efficient and discriminative.

For discriminative mapping, we exploit the marginal Fisher analysis (MFA) [33], which is a supervised manifold learning algorithm with Fisher criterion. It constructs the within-class graph $\mathcal{G}_{\mathrm{w}}$ and between-class graph $\mathcal{G}_{\mathrm{b}}$ considering both discriminant and geometrical structures in the data. Define the within-class affinity weight $s_{ij}^{(\mathrm{w})} = 1$ when $\mathbf{x}_i$ and $\mathbf{x}_j$ are k nearest neighbors of each other with the same class label; otherwise, $s_{ij}^{(\mathrm{w})} = 0$. Define symmetric matrix $\mathbf{S}_{\mathrm{w}}(i, j) = s_{ij}^{(\mathrm{w})}$, diagonal matrix $\mathbf{D}_{\mathrm{w}}(i, i) = \sum_j s_{ji}^{(\mathrm{w})}$, and Laplacian matrix $\mathbf{L}_{\mathrm{w}} = \mathbf{D}_{\mathrm{w}} - \mathbf{S}_{\mathrm{w}}$. Similarly, define the between-class affinity weight $s_{ij}^{(\mathrm{b})} = 1$ when $\mathbf{x}_i$ and $\mathbf{x}_j$ are k nearest neighbors of each other with different class labels; otherwise, $s_{ij}^{(\mathrm{b})} = 0$. Thus, $\mathbf{S}_{\mathrm{b}}$, $\mathbf{D}_{\mathrm{b}}$, and $\mathbf{L}_{\mathrm{b}}$ are obtained. The objective of MFA is to obtain the optimal projection vector $\mathbf{p}^*$ such that

$$\mathbf{p}^* = \operatorname*{argmin}_{\mathbf{p}} \frac{\mathbf{p}^T\mathbf{X}\mathbf{L}_{\mathrm{w}}\mathbf{X}^T\mathbf{p}}{\mathbf{p}^T\mathbf{X}\mathbf{L}_{\mathrm{b}}\mathbf{X}^T\mathbf{p}}.$$

Here, we use the optimal $\mathbf{p}^*$ as the basis for discriminative mapping of the facial makeup patterns after patch selection. This exploration of a discriminative mapping method for facial makeup detection is one of our novel contributions.

D. Using Makeup Detection for Automated Face Verification

The makeup detection result can help make it automatic for our correlation-based face authentication. The idea is that for a given pair of face images, we first perform makeup detection. If a face is detected to have makeup, it will be projected by using the correlation bases corresponding to the makeup class; otherwise, the bases corresponding to the nonmakeup class will be used for projection or feature transform. In this way, the correlation bases selection can be performed automatically and the process of face recognition can be executed automatically, without asking the user to provide the makeup or nonmakeup information. As a result, we can develop a complete framework for face authentication with an automated makeup detection, as shown in Fig. 4.

It is useful in practice to make the face recognition process automatic without user interaction. However, the accuracy of facial makeup detection will have a direct impact on correlation bases selection and the final face recognition accuracy as well. We need to investigate if the final accuracy of face recognition is influenced significantly or not, using the makeup detection result. We will validate this automated approach to face verification in our experiments.

IV. EXPERIMENTS

We validate our proposed methods experimentally. First, we introduce the database that we assembled for face recognition and makeup analysis. Second, we examine the face verification performance based on the three correlation methods on the whole face, local patch, and features, respectively. Different methods are compared for face verification. Third, facial makeup detection is executed. Finally, face verification based on the makeup detection result is presented.

A. Database

There are few publicly available databases containing both makeup and nonmakeup face images with a sufficient number of subjects to the best of our knowledge. To facilitate this paper, we assembled a face database of 1002 face images that is 501 pairs of female individuals. It contains mainly adult women of Asian or Caucasian descent, and is much larger than those datasets in [5], [16], and [29]. Each pair has a pair of one makeup and one nonmakeup face images of the same individual. All face images are collected from the Internet with text information about makeup or nonmakeup. So the labels of makeup and nonmakeup, and the facial identities, are collected together with the face images from the Internet. Some example face images from our database are shown in Fig. 1. From these examples, we can observe that there are also some other variations in addition to makeup, e.g., expressions, pose changes, and illumination variations. In this paper, we focus on the facial cosmetics in face verification.

We use five-fold cross validation for our experiments. Each pair of faces for an individual are either in the training or testing set in each round. There are about 4/5 individuals or face pairs in the training set and the remaining 1/5 are for testing in each case. The training and test sets are used for both face verification and makeup classification. There is no overlap between the training and test sets in each round. The average over the five rounds is used to measure the performance.

B. Face Verification Across Makeup

For face verification, we have about 100 pairs of positive faces for testing, while 400 pairs for training in each round. To have some negative pairs in testing, we randomly selected one face image from each of the remaining individuals in the test set. The random selection keeps the makeup and nonmakeup group information, i.e., if the face is nonmakeup under consideration, the randomly selected negative face will come from the makeup group. Therefore, our face matching is always between a pair of makeup and nonmakeup faces, no matter whether they are positive or negative pairs. The random pairing process was repeated for each individual. As a result, we have about 100 negative pairs of face images. In total, we have 200 pairs of faces for testing each time. This process is repeated five times to compute the average in our five-fold cross-validation scheme.

All faces are aligned based on the eye coordinates. The eyes can be detected by some existing methods [9]. Based on the eye centers, 12 patches, as shown in Fig. 3, are selected based on the relative locations. Then, various features will be extracted from the designated local patches in each face image. To show the importance of extracting features from local patches rather than the whole face, we compare the recognition accuracies in the two cases with a variety of features. The cosine distance (angular) measure is used for feature matching.

1) *Whole Face or Local Patches?:* First, we want to verify which is better for face verification: whole face or local patches? Using the same training and test image sets, we measure the face verification accuracies based on different methods, such as the PCA, HOG, and LBP, for feature extraction in the whole face images and local patches, respectively. We also used the PLS, CCA, and rCCA methods on raw images and local patches to compare the accuracies. The results are shown in Table I. Both the recognition accuracy and the area under the receiver operating curve (ROC), denoted by area under the ROC curve (AUC), are computed. Note that the accuracy and AUC are two different measures, which can be used to represent the authentication results from two aspects. For accuracy of computation, the threshold value is learned and adjusted in the tuning set, which is part of the training set (about 20% of the training data). The ROC curve characterizes the performance by computing the true-positive rate and false-positive rate using many different threshold values.

From Table I, we can observe several things.

a) The local patch-based approaches are usually better than the whole face images, especially for the PCA, HOG, LBP, and the PLS methods. For example, the accuracy for PCA is 64.0% when the whole face image is used, while it increases to 72.5% when the local patches are used. This result tells us that using local patches can reduce the influence of facial makeup on face recognition to some extent. Usually, the local patches are used to deal with head pose variation, but we show that local patches are also important to cope with facial makeup changes in face recognition.
b) The correlation methods, such as the PLS, CCA, and rCCA, cannot work well on raw images (whole images). For example, the PLS has an accuracy of 64.5% when the global raw images are used, which is lower than the PCA, HOG, and LBP. The three correlation methods have similar accuracies when the whole images are used.
c) Using local patches rather than the whole face image can improve the recognition accuracies for PLS, but not too much for the CCA and rCCA methods.
d) The PLS method can perform better than the CCA and rCCA methods when the local patches are used for face verification. For instance, the accuracy will be 71.5% for PLS, while only 66.5% for the CCA or rCCA.

2) *Correlations on Features:* We show that it is important to perform correlations on extracted features rather than on raw image patches. The results are shown in Table II. We observe that some high accuracies can be obtained when the correlations are executed on features, such as the PCA, HOG, and LBP. Using the PLS method on PCA feature, the verification accuracy can be as high as 81.5%, and 80.0% on the HOG feature. These accuracies are significantly higher

TABLE I

FACE VERIFICATION WITH DIFFERENT METHODS (PCA, HOG, AND LBP) FOR DIRECT FACE MATCHING, OR PLS, CCA, AND rCCA, FOR CORRELATION-BASED MATCHING, USING THE WHOLE FACE OR LOCAL PATCHES, RESPECTIVELY

	Whole face		Patch based	
	Accuracy	AUC	Accuracy	AUC
PCA	64.0%	0.68	72.5%	0.75
HOG	65.0%	0.66	71.5%	0.74
LBP	67.5%	0.68	69.5%	0.72
PLS	64.5%	0.65	71.5%	0.71
CCA	65.0%	0.65	66.5%	0.66
rCCA	65.0%	0.65	66.5%	0.66

TABLE II

COMPARISONS OF THE FACE VERIFICATION ACCURACIES USING THREE DIFFERENT CORRELATION TECHNIQUES (PLS, CCA, AND rCCA, RESPECTIVELY) ON THREE DIFFERENT FEATURES (PCA, HOG, AND LBP). THE PLS CORRELATION IS SIGNIFICANTLY BETTER THAN THE CCA AND rCCA ON ALL KINDS OF FEATURES

	PLS	CCA	rCCA
PCA	**81.5%**	72.5%	72.5%
HOG	**80.0%**	71.5%	71.5%
LBP	**76.0%**	70.0%	70.0%

TABLE III

IMPROVEMENT OF FACE VERIFICATION ACCURACIES WHEN THE PLS METHOD IS USED ON VARIOUS FEATURES (PCA, HOG, AND LBP, RESPECTIVELY). THE USE OF PLS CORRELATION CAN IMPROVE THE ACCURACIES SIGNIFICANTLY FOR VARIOUS FEATURES

	Accuracy without PLS	Accuracy with PLS
PCA	72.5%	81.5%
HOG	71.5%	80.0%
LBP	69.5%	76.0%

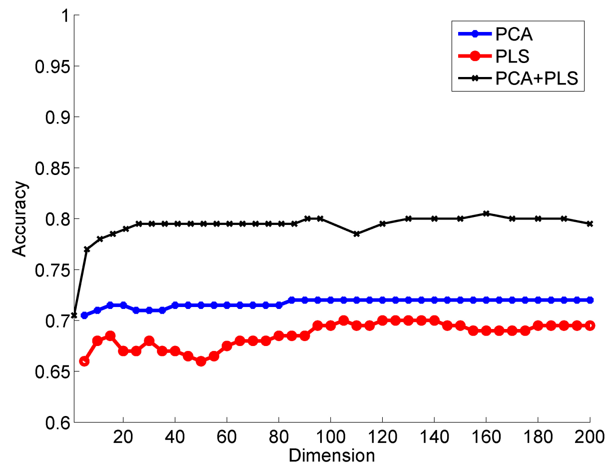


Fig. 5. Variations of face verification accuracies with respect to the dimensionality for three different methods: PCA, PLS, and PCA+PLS.

than the 71.0% based on the dual-attributes approach [30]. Comparing the first column in Table II with the first and fourth rows in Table I, the accuracy improvements are significant, using the combination of PCA+PLS or HOG+PLS.

Similarly, the CCA and rCCA methods can also have improved recognition accuracies, by looking at the second and third columns in Table II and comparing with the last two rows in Table I.

Another observation is that the LBP method performs worse than either the PCA or HOG method. Even with the correlation methods applied, the accuracies are still lower than the other two features, i.e., PCA and HOG, possibly because the facial makeup changes the facial skin texture significantly, which makes the LBP method being influenced more than the PCA and HOG methods.

3) *PLS Versus CCA and rCCA:* From Table II, the highest accuracy from CCA and rCCA is 72.5%, which does not improve over the result using just the PCA method, which is also 72.5% accuracy, as shown in Table I. As a result, the CCA and rCCA methods are not as good as the PLS method in face recognition across makeup.

Overall, the PCA+PLS approach performs the best in cross-makeup face verification. It is better than the single PCA or PLS only method, as shown in Fig. 5, or the ROC curves in Fig. 6. The HOG+PLS gives the second best result. To show the efficiency of the PLS method on various features, we extract the related results from Tables I and II, and show them in Table III. We can clearly see the importance and critical role of the PLS correlation on the three features.

C. Makeup Detection

In this experiment, we will empirically study the problem of facial makeup detection, which is to classify the face images into two classes: makeup and nonmakeup. We study what kinds of features are useful for makeup detection, and how to effectively use the related features to obtain a good performance.

Based on the knowledge about cosmetics, we propose to study four categories of features, i.e., skin color tone, skin smoothness, texture, and highlight, as stated in Section III-A. Through experimental validations and comparisons, we can understand what features are useful for makeup detection, how to use these features effectively, and if it is possible to combine these features together for a better performance.

Makeup detection itself can be considered an independent problem for facial image analysis or beauty analysis. It is also useful for our face verification problem. Based on the makeup detection result, the algorithm can determine which projection matrix to use for which face (makeup or nonmakeup) in correlation mapping, without asking the user to provide that information. We will show the corresponding result in the next subsection.

In the following, we study the proposed four categories of features separately. The training and test sets are the same as our face verification. There are about 4/5 faces for training and the remaining for testing in our five-fold cross validation. Unlike face authentication, we do not use negative pairs for makeup detection experiments. The support vector machines with RBF kernel [28] are used as the classifier.

1) *Skin Color Tone:* One purpose of using cosmetic products on faces is to change the skin color tone to make the face look younger and more beautiful. So our first feature

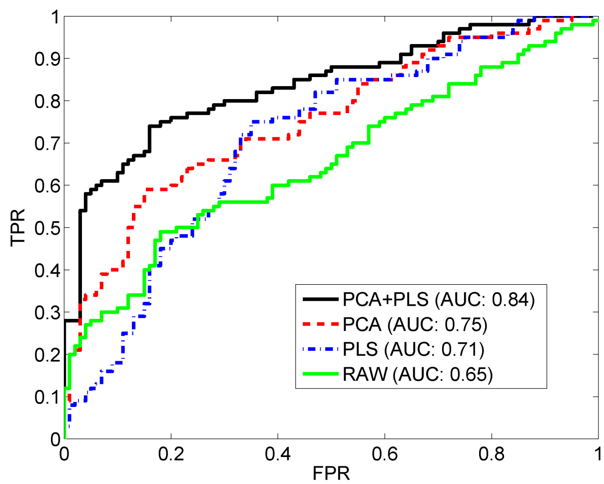


Fig. 6. ROC curves of face verification using different approaches. The AUC is also computed for each method.

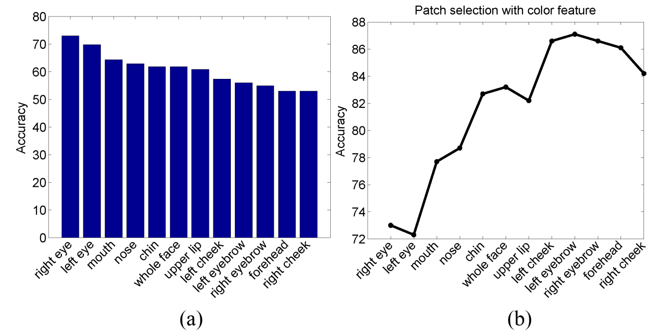


Fig. 7. Facial makeup detection using color feature. The RGB color space is used. (a) Recognition accuracy of the color feature on each local patch is sorted in descending order. (b) Accuracies of sequential adding of local patches based on the sorted patches are shown. The accuracy increases when more patches are added but drops when too many patches are used. The peak is selected based on our patch selection scheme.

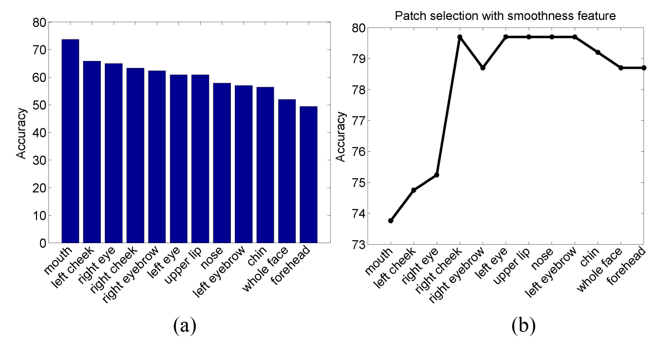


Fig. 8. Facial makeup detection using facial smoothness feature. (a) Recognition accuracy of the smoothness feature on each local patch is sorted in a descending order. (b) Accuracies of sequential adding of local patches based on the sorted patches. The accuracy increases when more patches are added. The peak is selected based on our patch selection scheme.

on makeup detection is about color. From each local patch in a face image, we compute the mean, standard deviation, and entropy in each of the three channels: red, green, and blue. Thus, there is a 9-D feature vector extracted from each local patch.

To understand the differences among the local patches in makeup detection, we use only one local patch each time for makeup classification. Then, the local patches are sorted in a descending order of accuracy. The result is shown in Fig. 7(a). We can observe that colors in regions of the eyes and mouth are the top patches. This result tells us that the eyes and mouth regions have more color changes between makeup and nonmakeup faces. There is a slight difference between left and right eyes, which is due to the existence of other variations in face images, such as pose, illumination. The colors in some other facial regions are also useful but with lower accuracies for makeup detection.

To explore how many local patches can be combined together to enhance the makeup detection performance, we perform patch selection, as stated in Section III-B. A greedy algorithm is used to select patches by adding one patch each time, starting from the most discriminative local patch first. The process of patch selection for the color feature is shown in Fig. 7(b). We can see that the accuracy increases by adding more patches, and reaches the peak when the six most accurate patches (out of 12) are combined together. This result shows that the patch selection is needed and that our scheme is effective to find the most useful local patches.

To show the results quantitatively, we put the makeup detection accuracies based on color in the first row of Table IV. When all patches are used, the makeup detection accuracy is 83.0%, which is increased to 85.0% when our patch selection scheme is executed. We also show that it is not good to use the whole face image. The accuracy reduces significantly to 55.5% when the whole face is used.

Next, we will perform a similar analysis for the other three features.

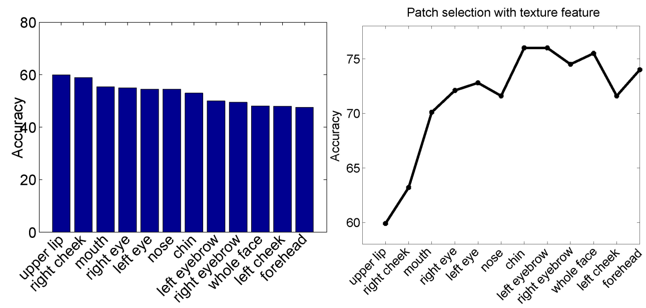
2) *Skin Smoothness:* The second category of features we explore is the facial skin smoothness. Women like to use makeup products to hide certain facial flaws, such as freckles, pimples, acne scars, wrinkles, and pores. In addition to making the face look younger and more beautiful, the makeup also makes the facial skin smoother. To separate makeup and nonmakeup faces, the skin smoothness feature may be useful.

To compute the skin smoothness, we use the intensity values from each local patch in a face image. As stated in Section III-A2, we compute the mean, standard deviation, and entropy of the intensity values in each local patch.

The results of patch sorting and patch selection based on the smoothness feature are shown in Fig. 8. We can observe that the top patches for smoothness measurements are different from those using color features. The number of the selected local patches is also different from the color features.

The quantitative results of the smoothness feature are shown in the second row of Table IV. When all patches are used, the makeup detection accuracy is 80.0%, which stays the same of 80.0% when our patch selection scheme is executed. Again, it is not good to use the whole face image. The accuracy reduces to 52.0% when the whole face is used for smoothness measure.

3) *Skin Texture:* In addition to skin smoothness change, cosmetic products may also change the facial skin texture. To explore this, we extract the texture feature for the separation of makeup and nonmakeup faces. Since the LBP feature is



(a) (b)

Fig. 9. Facial makeup detection using facial texture feature. The LBP is used to characterize the texture. (a) Recognition accuracy of the texture feature on each local patch is sorted in a descending order. (b) Accuracies of sequential adding of local patches based on the sorted patches. The accuracy increases when more patches are added but drops when too many patches are used. The peak is selected based on our patch selection scheme.

usually used for facial texture characterization for face recognition, we use the LBP texture feature for makeup detection, as stated in Section III-A3. The LBP feature is computed in each local patch of image intensities.

The results of patch sorting and patch selection based on the texture feature are shown in Fig. 9. We can observe that the top patches for texture measures are different from those using color or smoothness features. Two most accurate local patches are selected to achieve the highest accuracy in the patch selection process.

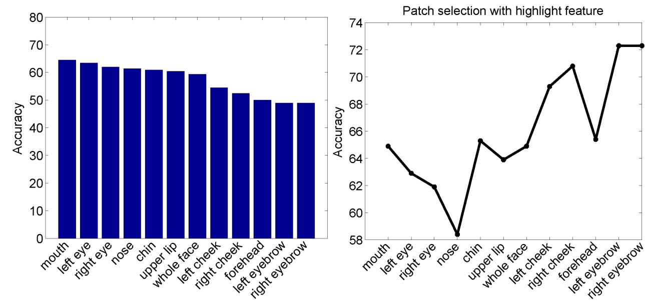
The quantitative results of the texture feature are shown in the third row of Table IV. When all patches are used, the makeup detection accuracy is 81.0%, which is increased to 85.0% when the patch selection scheme is executed. When the whole face image is used for texture measure, the accuracy reduces to a lower value of 72.5%.

4) *Highlight:* The last category of features that we explore is the facial highlight. Intuitively, the diffuse reflection and highlight distributions may be different in makeup and nonmakeup faces. Based on this, we compute the highlight in each face image based on the dichromatic reflection model and extract features to characterize the highlight from each patch in a face image, as stated in Section III-A4.

The results of patch sorting and patch selection based on the highlight feature are shown in Fig. 10. We can see the top patches for highlight measure and the accuracy variation during the patch selection process. To reach a high accuracy, six patches are selected as the most accurate, which are different from the color, smoothness, or texture features individually.

The quantitative results of the highlight feature are shown in the last row of Table IV. When all patches are used, the makeup detection accuracy is 64.5%, which is increased to 68.5% based on patch selection. It is still not good to use the whole face for highlight characterization, since the accuracy reduces to 52.5% in that case.

Overall, we have shown that several kinds of features can be extracted for classification of makeup and nonmakeup faces. All of these features perform much better than a random guess, which is 50% accurate. Therefore, makeup detection in face images can be executed. Furthermore, our patch selection



(a) (b)

Fig. 10. Facial makeup detection using facial highlight feature. The highlight is extracted in each face image. (a) Recognition accuracy of the highlight feature on each local patch is sorted in a descending order. (b) Accuracies of sequential adding of local patches based on the sorted patches.

TABLE IV

FACIAL MAKEUP DETECTION ACCURACIES USING FOUR DIFFERENT CATEGORIES OF FEATURES IN THREE DIFFERENT CASES: 1) WHOLE FACE; 2) ALL LOCAL PATCHES; AND 3) SELECTED PATCHES

	Whole face	All patches	Patch selection
Color	55.5%	83.0%	85.0%
Smoothness	52.0%	80.0%	80.0%
Texture	72.5%	81.0%	85.0%
Highlight	52.5%	64.5%	68.5%

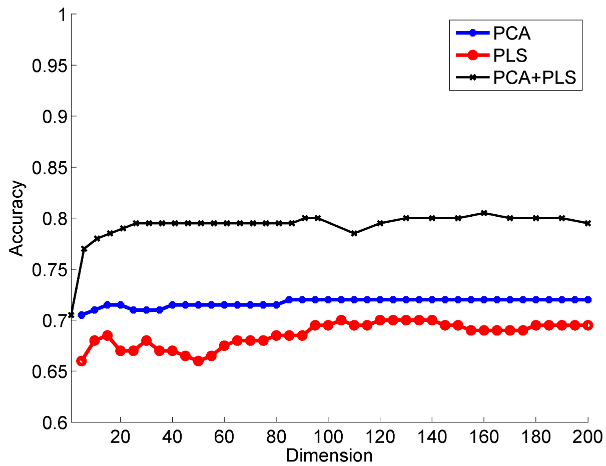
scheme is effective to improve the recognition accuracies. The next questions are: 1) Can we make these features more discriminative? 2) Can we combine the different features together? We will address them in the following.

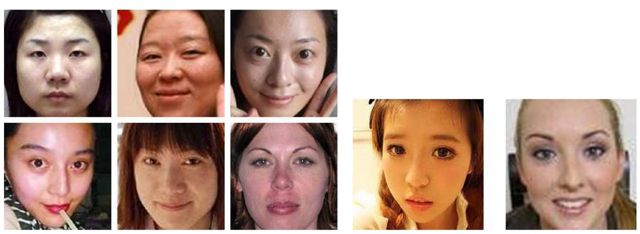
5) *Discriminative Mapping:* We explore a discriminative mapping approach to combine the selected patches with different features together, and make them more discriminative. To verify the idea, we apply the MFA method introduced in Section III-C.

The results are shown in Table V. We found that the discriminative mapping by the MFA can improve the color feature for makeup detection from 85.0% to 88.0%. Combining color and smoothness features can further improve the makeup detection accuracy to 96.0%, which is the highest accuracy we obtain. On the other hand, when all four features are concatenated together and then mapped discriminatively by the MFA method, the accuracy is 92.5%, which is higher than each single feature, i.e., color, smoothness, texture, and highlight, but is still lower than the color and smoothness feature combination. We also tried to use other feature combinations, such as those shown in Table V, but there is no accuracy that can be higher than the 96.0%. Based on this result, we observe that the color and smoothness features can complement each other and their combination with discriminative mapping performs significantly better than other combinations for makeup detection. The texture feature itself can get a high accuracy, but its combination with other features cannot reach the highest accuracy.

In summary, the combination of color and smoothness features is the best for makeup detection in our current experiment. A discriminative mapping via the MFA method can improve it to a high accuracy of 96.0%. Other features are

TABLE V
FACIAL MAKEUP DETECTION ACCURACIES USING DISCRIMINATIVE MAPPING BY THE MFA METHOD. EACH FEATURE IS BASED ON PATCH SELECTION





(a) (b)

Fig. 11. Faces of wrong classification results. (a) Six nonmakeup faces incorrectly classified as makeup. (b) Two makeup faces incorrectly classified as nonmakeup.

useful for makeup detection; however, their performance is not as good as the color and smoothness combination. The texture and highlight cues may not be sufficiently complementary to the color and smoothness cues, and thus the combination of all of these cues gives a lower accuracy than using the color and smoothness cues.

We show the results of wrong classification face images in Fig. 11. There are six nonmakeup face images incorrectly classified as makeup [Fig. 11(a)], while two makeup faces incorrectly classified as nonmakeup [Fig. 11(b)]. The reasons may include low image quality, and expression and pose changes. Sometimes, it is even challenging for human perception to separate makeup and nonmakeup faces.

Based on the makeup detection result, we can examine its impact on our face recognition system next.

D. Automated Face Verification With Makeup Detection

In our face verification experiments in Section IV-B, we assume that the makeup or nonmakeup information is known for each face image for correlation mapping (e.g., the PLS method). Based on our makeup detection experiments presented in Section IV-C, we can use the computer recognized makeup or nonmakeup information for correlation mapping. If a face is classified as a nonmakeup face, it will use the projection matrix corresponding to nonmakeup set. Otherwise, the projection matrix for makeup set is used. Now the problem is, how accurate the face verification can achieve based on the makeup detection result.

TABLE VI
FACE VERIFICATION ACCURACIES OF THE PLS METHOD ON VARIOUS FEATURES (PCA, HOG, AND LBP, RESPECTIVELY) BASED ON THE AUTOMATED FACIAL MAKEUP DETECTION RESULT

	Face Verification Accuracy with Makeup Detection
PCA+PLS	80.5%
HOG+PLS	80.0%
LBP+PLS	72.0%

Since the correlation mapping based on the PLS method is better than the CCA and rCCA methods, we only use the PLS method for this experiment. Based on the 96.0% accuracy of makeup detection, the face verification accuracies are shown in Table VI. The correlation with PLS is applied to different features in local patches, including the PCA, HOG, and LBP features. By comparing Tables III and VI, we found that the face verification accuracies do not drop significantly for the PCA and HOG features, but it does change from 76.0% to 72.0% for the LBP feature. This also indicates that the makeup changes the facial texture that reduces the LBP performance. In contrast, even with the automated makeup detection, our system can still get a good performance, e.g., an 80.5% accuracy using the PCA+PLS method, and an 80.0% accuracy based on the HOG+PLS method.

As a result, we have shown that our makeup detection approach is effective, and that the accuracy of face verification with cosmetic changes can be as high as 80.5%, when proper methods are developed.

V. CONCLUSION

We have studied the problem of face recognition with cosmetic changes. A database of about 500 pairs of face images (makeup and nonmakeup) was collected to facilitate our study. To deal with the facial changes with makeup, we have proposed to use correlation mapping between the makeup and nonmakeup faces on features extracted from local patches. The learned correlation bases can be used to project faces in different appearances separately, and the transformed features for faces belonging to the same identity are moved closer in the new feature space. We have found that the correlation has to be executed on extracted features, rather than on raw images. The local patch-based feature extraction and correlation mapping are crucial, which can tolerate the diversity of users who apply cosmetic products with different styles or degrees. Three methods have been explored for correlation mapping, and we found that the PLS method performs better than the CCA or rCCA.

We have also studied the problem of makeup detection. Based on the knowledge of how to apply cosmetics, we have proposed to investigate four categories of features, including facial skin tone, skin smoothness, texture, and highlight. These features are computed in local patches of face images. We have presented a patch selection scheme and discriminative mapping to improve the makeup detection accuracies effectively. We have found that the color feature combined with smoothness performs better than others for makeup characterization. A high accuracy of 96.0% has been achieved.

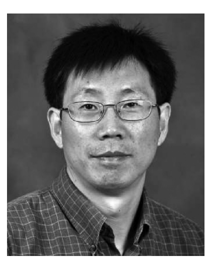
Finally, we have presented a complete system that can perform automated face verification utilizing the makeup detection result. The correlation mapping can be applied to the classified makeup or nonmakeup faces automatically without user interaction. A high accuracy of about 80.0% can be obtained for automated face authentication in conjunction with a makeup detection scheme.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their helpful suggestions to improve this paper.

REFERENCES

[1] P. Private, *et al.*, (2011, May). *How to Apply Makeup* [Online]. Available: http://www.wikihow.com/Apply-Makeup
[2] L. Adkins and R. Adkins, *Handbook to Life in Ancient Greece*. Oxford, U.K.: Oxford Univ. Press, 1998.
[3] T. Ahonen, A. Hadid, and M. Pietikainen, "Face recognition with local binary patterns," in *Proc. Eur. Conf. Comput. Vision*, 2004, pp. 469–481.
[4] B. Burlando, L. Verotta, L. Cornara, and E. Bottini-Massa, *Herbal Principles in Cosmetics: Properties and Mechanisms of Action*, vol. 8. Boca Raton, FL, USA: CRC Press LLC, 2010.
[5] C. Chen, A. Dantcheva, and A. Ross, "Automatic facial makeup detection with application in face recognition," in *Proc. ICB*, Jun. 2013, pp. 1–8.
[6] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *Proc. IEEE Conf. Comput. Vision Pattern Recognit.*, 2005, pp. 886–893.
[7] A. Dantcheva, C. Chen, and A. Ross, "Can facial cosmetics affect the matching accuracy of face recognition systems?" in *Proc. IEEE Conf. Biometrics Theory Appl. Syst.*, 2012, pp. 391–398.
[8] A. Dantcheva and J. Dugelay, "Female facial aesthetics based on soft biometrics and photo-quality," in *Proc. IEEE Conf. Multimedia and Expo.*, 2011, pp. 1–6.
[9] M. Everingham, J. Sivic, and A. Zisserman, "Hello! My name is... Buffy—Automatic naming of characters in TV video," in *Proc. Brit. Mach. Vision Conf.*, 2006, pp. 801–908.
[10] N. Guéguen, "The effects of women's cosmetics on men's courtship behavior," *North Amer. J. Psychol.*, vol. 10, no. 1, pp. 221–228, 2008.
[11] D. Hardoon, C. Saunders, S. Szedmak, and J. Shawe-Taylor, "A correlation approach for automatic image annotation," in *Proc. ADMA*, LNAI 4093. 2006, pp. 681–692.
[12] D. Hardoon, S. Szedmak, and J. Shawe-Taylor, "Canonical correlation analysis: An overview with application to learning methods," *Neural Comput.*, vol. 16, no. 12, pp. 2639–2664, 2004.
[13] H. Hotelling, "Relations between two sets of variates," *Biometrika*, vol. 28, no. 3, pp. 312–377, 1936.
[14] T.-K. Kim, S.-F. Wong, and R. Cipolla, "Tensor canonical correlation analysis for action classification," in *Proc. CVPR*, 2007, pp. 1–8.
[15] A. Li, S. Shan, X. Chen, and W. Gao, "Maximizing intra-individual correlations for face recognition across pose differences," in *Proc. CVPR*, 2009, pp. 605–611.
[16] R. Ohtsuki, S. Tominaga, and R. Hikima, "Appearance analysis of human skin with cosmetic foundation," in *Proc. IS&T/SPIE Electron. Imaging*, vol. 8292. Jan. 2012, pp. 82920Q-1–82920Q-8.
[17] G. Rhodes, A. Sumich, and G. Byatt, "Are average facial configurations attractive only because of their symmetry?" *Psychol. Sci.*, vol. 10, no. 1, pp. 52–58, 1999.
[18] R. Rosipal, "Nonlinear partial least squares: An overview," in *Chemoinformatics and Advanced Machine Learning Perspectives: Complex Computational Methods and Collaborative Techniques* (ACCM), H. Lodhi and Y. Yamanishi, Eds. IGI Global, Hershey, PA, USA, 2011, pp. 169–189.
[19] R. Rosipal and N. Kramer, "Overview and recent advances in partial least squares," in *Subspace, Latent Structure and Feature Selection Techniques*, C. Saunders, M. Grobelnik, S. Gunn, and J. Shawe-Taylor, Eds. Berlin, Germany: Springer, 2006, pp. 34–51.
[20] W. Schwartz, H. Guo, and L. Davis, "A robust and scalable approach to face identification," in *Proc. ECCV*, Sep. 2010, pp. 476–489.
[21] S. Shafer, "Using color to separate reflection components," *Color Res. Appl.*, vol. 10, no. 4, pp. 210–218, 1985.
[22] A. Sharma, M. Haj, J. Choi, L. Davis, and D. Jacobs, "Robust pose invariant face recognition using coupled latent space discriminant analysis," *Comput. Vision Image Understanding*, vol. 116, no. 11, pp. 1195–1110, 2012.
[23] A. Sharma and D. Jacobs, "Bypassing synthesis: PLS for face recognition with pose, low-resolution and sketch," in *Proc. CVPR*, 2011, pp. 593–600.
[24] L. Sun, S. Ji, and J. Ye, "Canonical correlation analysis for multilabel classification: A least-squares formulation, extensions, and analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 1, pp. 194–200, Jan. 2011.
[25] R. Tan and K. Ikeuchi, "Separating reflection components of textured surfaces using a single image," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 2, pp. 178–193, 2005.
[26] M. Turk and A. Pentland, "Eigenfaces for recognition," *J. Cognitive Neurosci.*, vol. 3, no. 1, pp. 71–86, 1991.
[27] S. Ueda and T. Koyama, "Influence of make-up on facial recognition," *Perception*, vol. 39, no. 2, p. 260, 2010.
[28] V. N. Vapnik, *Statistical Learning Theory*. New York, NY, USA: Wiley, 1998.
[29] S. Varshovi, "Facial makeup detection using HSV color space and texture analysis," Master's thesis, Dept. Comput. Sci. Software Eng., Concordia Univ., Montreal, QC, Canada, 2012.
[30] L. Wen and G.-D. Guo, "Dual attributes for face verification robust to facial cosmetics," *J. Comput. Vision Image Process.*, vol. 3, no. 1, pp. 63–73, 2013.
[31] H. Wold, "Path models with latent variables: The NIPALS approach," in *Quantitative Sociology: Internnational Perspectives on Mathematical and Statistical Model Building*, H. M. Blalock, A. Aganbegian, F.M. Borodkin, R. Boudon and V. Capecchi, Eds. San Francisco, CA, USA: Academic, 1975, pp. 307–357.
[32] H. Wold, "Partial least squares," in *Encyclopedia of Statistical Sciences*, vol. 6, S. Kotz and N. Johnson, Eds. New York, NY, USA: Wiley, 1985, pp. 581–591.
[33] S. Yan, D. Xu, B. Zhang, H. Zhang, Q. Yang, and S. Lin, "Graph embedding and extensions: A general framework for dimensionality reduction," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 1, pp. 40–51, Jan. 2007.
[34] Q. Yang, S. Wang, and N. Ahuja, "Real-time specular highlight removal using bilateral filtering," in *Proc. 11th Eur. Conf. Comput. Vision*, 2010, pp. 87–100.



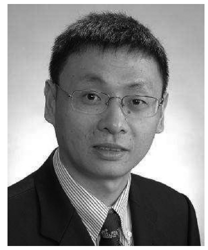
Guodong Guo (M'07–SM'07) received the B.E. degree in automation from Tsinghua University, Beijing, China, in 1991, the Ph.D. degree in pattern recognition and intelligent control from Chinese Academy of Sciences, Beijing, China, in 1998, and the Ph.D. degree in computer science from University of Wisconsin-Madison, Madison, WI, USA, in 2006.

He is an Assistant Professor with the Lane Department of Computer Science and Electrical Engineering, West Virginia University (WVU), Morgantown, WV, USA. In the past, he visited and worked in several places, including INRIA, Sophia Antipolis, France; Ritsumeikan University, Kyoto, Japan; Microsoft Research, Beijing, China; and North Carolina Central University, Durham, NC, USA. He authored a book, *Face, Expression, and Iris Recognition Using Learning-Based Approaches*, in 2008 and has published over 60 technical papers in face, iris, expression, gender recognition, age estimation, and multimedia information retrieval. His research interests include computer vision, machine learning, and multimedia.

Dr. Guo received the North Carolina State Award for Excellence in Innovation in 2008 and the Outstanding New Researcher of the Year in 2010 to 2011 at WVU. He was selected as a People's Hero of the Week by Broadband and Social Justice Blog (BSJB) under Minority Media and Telecommunications Council (MMTC) on July 29, 2013.

Lingyun Wen received the B.S. degree in computer science from Shandong Normal University, Jinan, China, in 2006 and the M.S. degree in computer science from University of Science and Technology of China, Hefei, China, in 2009.

She was a Research Engineer in Beijing, China, from 2009 to 2010. She currently is a Graduate Student with the Lane Department of Computer Science and Electrical Engineering, West Virginia University, Morgantown, WV, USA. Her research interests include computer vision and machine learning.



Shuicheng Yan (M'06–SM'09) is an Associate Professor with the Department of Electrical and Computer Engineering, National University of Singapore, Singapore, and the Founding Leader of the Learning and Vision Research Group (http://www.lv-nus.org). He has authored and co-authored over 330 technical papers over a wide range of research topics, with more than 9500 Google Scholar citations and H-index-42. His research interests include computer vision, multimedia, and machine learning.

Mr. Yan is an Associate Editor of IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY and *ACM Transactions on Intelligent Systems and Technology*. He has been the Guest Editor of special issues for IEEE TRANSACTIONS ON MULTIMEDIA (TMM) and COMPUTER VISION AND IMAGE UNDERSTANDING (CVIU). He received the Best Paper Awards from ACM MM12 (demo), PCM'11, ACM MM10, ICME10, and ICIMCS'09; the Winner Prizes of the classification task in PASCAL VOC 2010–2012; the Winner Prize of the segmentation task in PASCAL VOC 2012; the Honorable Mention Prize of the detection task in PASCAL VOC'10; the 2010 TCSVT Best Associate Editor Award; the 2010 Young Faculty Research Award; the 2011 Singapore Young Scientist Award; and the 2012 NUS Young Researcher Award.