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Face Authentication and Makeup detection

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Abstract –*Facial makeup has the ability to alter the appearance of a person. It reduces accuracy of face recognition system. To develop a face recognition system that is potent to facial makeover, we extract feature from local patches of face and perform correlation mapping between non-makeup and makeup face with the help of PCA (Principal Component Analysis). Skin color tone, skin smoothness, texture and highlight are the major aspects of facial makeup. Using these all feature we calculate the attribute difference between the faces. The performance of the system gets improved by using patch selection scheme and discriminative mapping techniques. A complete system is then developed for face verification utilizing the makeup detection result. The combination of PCA+PLS approach gives high reliability to the system. We experiment the system on a large dataset of images up to 500 pairs.*

Key Words: *Local patches, Partial Least Square, Correlation Mapping, and Principal Component Analysis.*

1. INTRODUCTION

Many real applications make use of human face recognition. Lots of research has been done in this domain to acquire high performance. In recent studies [7], [15], it has been manifest that heavy makeup creates problem for humans to recognize faces. Also the impact of facial makeup on face recognition has been presented [5]. Present face recognition methods are based on contrast and texture information, and it can be impacted by the application of facial makeup.

In reality, to hide facial flaws and to look beautiful most women wear cosmetic. Facial cosmetics or makeup can alter the perceived appearance of person [5], [7], [15]. Figure.1 shows the pairs of face images of same individual with makeup or without makeup.

Fig -1: Pairs of face images of the same individuals in makeup or non-makeup showing significant appearance changes.

In order to develop a potent system for face recognition, the influence affected by cosmetic products needs to be considered. To learn facial attributes in makeup and non-makeup faces separately, a dual attributes approach [17] was introduced which uses semantic-level attributes to reduce the effect of makeup. Later, a self-quotient image technique [3] was proposed to pre-process. And it eliminates the impact of makeup before face image matching. But these methods are still not more significant.

In our paper, we explore a correlation-based scheme for makeup invariant face authentication. Two face images of same person are highly correlated even if the makeup is applied or not while different person should not have the maximum correlation. The key approach is to build a relationship for two face images of same person, even if having different degree of makeup, e.g., with or without. The projection of makeup and non-makeup faces is done respectively on the basis of learned correlation. It will have more similar features in the transformed feature space if the faces are of same person. The basic framework of our proposed approach can be illustrated in Fig. 2.

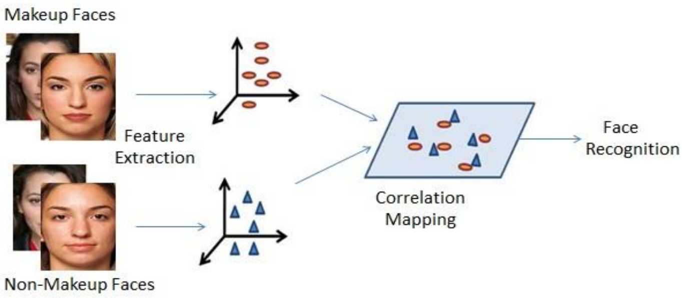

Fig -2: Basic framework that we propose for face recognition that is potent to cosmetic changes based on a correlation mapping.

We also searched for some recent work related to makeup detection problem. We studied the appearance of cosmetics foundation on face images with the help of multiband camera system and the oily-shine regions in makeup face images. These oily-shine regions were detected using clustering method [6]. But in [6] it does not provide the result on classification of makeup and non-makeup face. A system was introduced in [16] to detect eye-shadow, lipstick and foundation. It used both texture features and HSV color space model. However, the classification between makeup and non-makeup faces is not provided also in [16]. Taking motivation from the work in [16], Chen et al. [3] explored the system which was using shape, texture and color features and also providing binary classification of non-makeup and makeup faces. Though work in [3] is somewhat similar to our approach, there are significant differences. The system in [3] was using only three patches whereas we use 12 local facial patches and consider more makeup cues. To obtain high accuracy for makeup detection, we explore patch selection and discriminative mapping methods which was not used in [3].

To characterize facial makeup, four categories are presented based on how humans apply makeup. Patch selection and discriminative mapping enhance the makeup detection performance. A complete system can be developed for face verification by using makeup detection results. This system provides the automatic selection of correlation bases without much human intervention. Following are the major aspects of the system.

1. We explore a method which uses correlation of local patches obtained from face images, to authenticate the face. This method is robust to cosmetic changes.
2. We develop a method to detect facial makeup, which is useful itself for facial analysis, and provides the amount of difference between both faces with respect to makeup.

In the remaining, we introduce various approaches in potent face verification in chapter 2. Then, we provide the characterization of facial makeup in chapter 3 and finally makeup detection is discussed in chapter 4. And hence we can develop a complete framework for face authentication with automated makeup detection, as shown in Fig. 3.

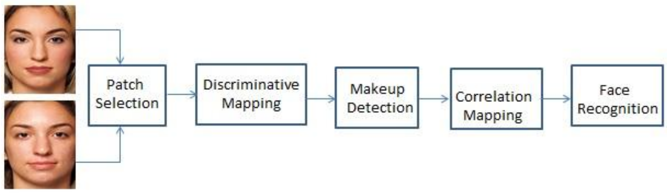

Fig -3: Complete framework of integrated makeup detection and face verification.

2. Potent Face Verification

2.1 Partial Least Squares

PLS (Partial Least Squares) models relationship between set of independent observed variables by means of latent variables [8], [9], and [19]. A PLS model will try to find the multidimensional direction in the *X* space that explains the maximum direction in the *Y* space. When independent observed variables are extremely correlated, it has been shown to be a powerful technique.

PLS method depends on the assumption that the independent data is generated by a system containing number of latent variables.

Suppose there are two data sets A and B contains n data samples, where $A \subset R^M$ and $B \subset R^N$.
R^M and R^N stand for M-dimensional and N-dimensional spaces respectively.
The relations between A and B in PLS methods of latent vectors such that

$$A = XP\,X + E$$
$$B = YQ\,X + F \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

Where X and Y are extracted from latent vectors, P and Q represent matrices of storing and the E and F are the matrices of unused.

The PLS method uses a greedy strategy to find multiple basis vectors that project A and B to a score space. It is based on nonlinear constant partial least squares (NCPALS) algorithm to find weight vectors w, c to satisfy

$$[\mathrm{cov}\ (t, u)]^2 = [\mathrm{cov}(X_w, Y_c)]^2$$
$$= \max_{|r|=|s|=1} [\mathrm{cov}(X_r, Y_s)]^2$$

$$\text{where} \quad [\mathrm{cov}(\mathbf{t}, \mathbf{u})]^2 = \frac{t^T \mathrm{u}}{\mathrm{n}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Denotes the sample covariance between the score vectors t and u [8].For regression or classification problems the PLS methods were derived [9], [18], [19].For face verification under cosmetic changes, we explore the PLS method for a new problem, where both X and Y are face images in makeup and non-makeup groups.

2.2 Correlation on Facial Features

We propose to use a correlation on facial characteristics to develop a potent face recognizer. The correlation methods applied to the extracted features in face images than pixel values, because facial cosmetics may change the facial expressions in terms of single pixel values. For different individuals and different facial parts, the pixel values may be changed.

The LBP (local binary patterns) [2] and the HOG (histogram of oriented gradient) [4] are the methods used for facial feature representation. The PCA (principal component analysis) can compute the Eigen-faces [14] for facial feature characterization. The principal components of PCA are unrelated because they are the Eigen vectors of the covariance matrix which is symmetric. In Eigen faces [14], the projection coefficients are used as features for face representation.

The PLS or CCA correlation is applied on raw face images which is in previous approaches [10], [12]. Our problem of face authentication and makeup detection with facial makeup changes has some properties. The direct correlation on raw pixels values has a lower accuracy in [10] and [12].

2.3 Local Patches

Local patches are used in extracting features and the correlations mapping approach which are the main aspects of facial makeup detection. Correlation mapping on extracted features is more convenient than that of on raw pixels. We can notice that different facial parts could be applied with different cosmetic products and foundations with different amounts or degrees over each other. For example, the eye makeup can have different colors (e.g., bronze, gold smoky) used to look the eyes attractive and more youthful. Whereas red or other bright colors may be applied to the lips to reshape (e.g., bring balance to the lips) to have a beautiful look. It is hard to learn a correlation and mapping of global faces between non makeup and makeup face images. To make it easier we use local patches obtained from face images. Local patches provide another advantage which makes the approach robust to facial expression changes, variations in illumination and poses. As a result, both the correlation learning and feature extraction are processed on the basis of local patches, instead of global face image. The patches we use in each face image are illustrated in Fig. 4.

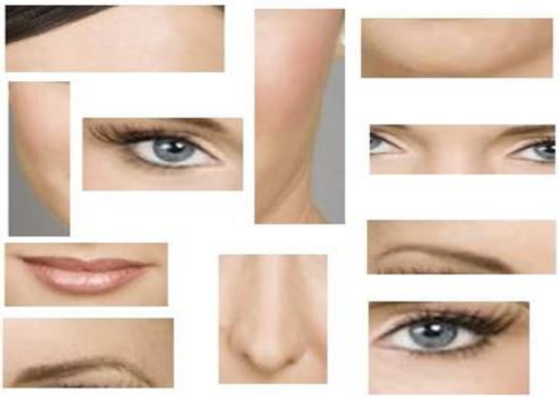

Fig -4: Facial patches

3. Characterization of Facial Makeup

Four methods can be explored in order to characterize the facial makeover based on the research in cosmetic domain [1].

3.1 Skin Smoothness

When makeup is applied, the smoothness of face may get changed. The appearance gets alter after applying some foundation creams or other products and skins becomes smoother. Hence, the measure of skin smoothness affects the facial characteristics. Only the image intensity values are used within each patch in a face image. For calculating the separation of makeup and non-makeup image features based on skin smoothness, we compute same as skin color tone but in image patch intensities only. As formulas given above for mean, standard deviation, and entropy we can measure the smoothness difference.

3.2 Skin Color Tone

The facial skin color tone plays an important role in makeup characteristics of face. After applying cosmetics on the face the color of face may get changed. Some cosmetic products use colorants that are coated with waxy or gel-like properties. When the product is applied on your skin the friction breaks open the dye capsules releasing the color. Person looks more beautiful and younger, the result of skin color tone [1]. Thus, we can characterize the difference between makeup and without makeup face based on the color tone of skin of faces. For calculating the color tone difference we mainly use three approaches, mean, standard deviation and entropy. In the following formula it is denoted as μ, σ, and E, respectively, to characterize the skin color tone in each of the three color channels (Red, Green, and Blue). Then features are extracted (almost nine) for each patch in the image.

Suppose the histogram of pixels resulting from each patch is denoted by H (i), where i is the index of pixel value. N is the number of pixels in each patch. Then, the mean, standard deviation and entropy is computed for each patch using following formula:

$$\mu_c = \sum_i H(i) * i \quad \text{…………..……………………………(3)}$$

$$\sigma_c = \sqrt{\sum_i \ (i-\mu)^2 * H(i)} \quad \text{……………..……..(4)}$$

$$E_c = -\sum_i H(i) \log_2 H(i) \quad \text{………………..…......(5)}$$

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

3.3 Texture

Skin texture varies from skin type to skin type like oily and dry skin and person to person. To enhance the skin texture there are wide range of products are available in the market which affects the skin makeup. We can combine this texture with smoothness of skins but we want separate skin texture feature specifically. For this we explore the method called LBP [2], which is very simple method to process out texture features. In this method the intensity of center pixel is compared with neighboring pixels. A small neighborhood (3×3) is utilized in our LBP texture feature extraction. The binary patterns are basically encoded with eight bits and for each patch image we calculate the LBP features.

3.4 Highlight

The facial highlight makes huge difference between makeup and without makeup face. Characterizing the highlights result in variation of face makeovers. The foundation products can change the skin highlights very effectively [6]. To utilize this we first compute facial highlights in face images and then extract related features to characterize the highlight component for makeup detection. In this, for facial reflections, we adopt the dichromatic reflection model [16]. It is a simply combination of diffuse I^D and specular I^S components, where I is the light color (reflected) at every pixel.

$$I = I^D + I^S \quad \ldots\ldots (6)$$

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

$$\sigma_c = \frac{I_c}{\sum_{c \in \{r,g,b\}} I_c} \quad \ldots\ldots (7)$$

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

$$\Lambda_c = \frac{I_c^D}{\sum_{c \in \{r,g,b\}} I_c^D}, \quad \Gamma_c = \frac{I_c^S}{\sum_{c \in \{r,g,b\}} I_c^S} \quad \ldots\ldots (8)$$

The maximun chromaticity can be defined [25] by

$$\sigma_{\max} = \max\{\sigma_r, \sigma_g, \sigma_b\} \quad \ldots\ldots (9)$$

And similarly for maximum diffuse chromaticity by

$$\Lambda_{max} = \max\{\Lambda_r, \Lambda_g, \Lambda_b\} \quad \ldots\ldots (10)$$

Then, the diffuse component can be computed by

$$I_c^D(\Lambda_{max}) = I_c - \frac{\max_{c \in \{r,g,b\}} I_c - \Lambda_{max} \sum_{c \in \{r,g,b\}} I_c}{1 - 3\Lambda_{max}} \quad \ldots\ldots (11)$$

According to [13]. Therefore, the highlight detection problem can be triggered as the searching for the maximum diffuses chromatically max, which changes from pixel to pixel [13]. In max estimation bilateral filtering can be used to improve performance. The resulting detected highlight, we can measure the variation by computing the mean, standard deviation, and entropy, in each of the independent patches in the highlight image, using methods similar to (3), (4), and (5).

4. Makeup Detection

Our approach is to classify the face images into makeup and non-makeup class. For this we study the makeup detection problem. As makeup detection result provides the automated selection of correlation bases for feature projection, it plays an important role in face authentication and makeup changes. Various cues can be built to characterize the makeup computationally on the basis of how humans apply the cosmetics. Then next steps are patch selection and discriminative mapping discussed below.

4.1 Patch Selection

In previous chapter four different ways to characterize facial makeup were introduced which are skin color tone, skin texture, skin smoothness and highlight. In each facial patch every feature is computed independently. We noticed that when these feature are computed in whole face image, the performance was lagging this might be happened because of using cosmetic products differently on different facial parts and the cosmetic effect may be more significant on some parts then others.

Therefore we emphasize the use of local patches for facial makeup characterization. The designated facial patches might not be equally useful for facial makeup detection. So to explore this, Patch selection is performed using a greedy method. In this method, the accuracy or capability of each patch is measured for facial makeup detection. Then on the basis of classification accuracies of patches, all patches are sorted in a descending order. We sequentially add patches, one by one from the rank one patch. Then major the accuracy of patch again when each new patch is added in the list of patches. The similar procedure is followed until all patches are added.

Then the peak value of highest accuracy is selected to obtain the appropriate number of patches. After this peak value is used again to determine which patches to use for facial makeup classification. This process is done for skin color, texture, skin smoothness, highlight separately. Hence by using this greedy search method, we can find all useful patches in each feature representation.

4.2 Discriminative Mapping

After the patch selection process we obtain the useful patches for makeup classification. Though we obtain useful patches, there are still two things to consider:

1. If the features on the selected patches can be integrated with each other.
2. If the features on the selected patches can be made more discriminative in order to improve the recognition accuracy.

Therefore to address this, we will combine the selected patches with each corresponding feature and use a discriminative mapping method make combination more efficient and discriminative. In discriminative mapping we exploit the MFA (Marginal Fisher Analysis) [20], which is a supervised manifold learning algorithm with fisher criterion. Two class graphs are constructed in this method. These graphs are within-class graph $\mathbf{G}_w$, between-class graph $\mathbf{G}_b$ respectively. These graphs are constructed by considering discriminant and geometrical structures in the data.

Define the within-class affinity weight $s_{ij}^{(w)} = 1$ when $\mathbf{x}_i$ and $\mathbf{x}_j$ are k nearest neighbors of each other with the same class label; otherwise, $s_{ij}^{(w)} = 0$. Define symmetric matrix $\mathbf{S}_w(i, j) = s_{ij}^{(w)}$, diagonal matrix $\mathbf{D}_w(i, i) = \sum_j s_{ij}^{(w)}$, and Laplacian matrix $\mathbf{L}_w = \mathbf{D}_w - \mathbf{S}_w$. Similarly, define the between-class affinity weight $s_{ij}^{(b)} = 1$ when $\mathbf{x}_i$ and $\mathbf{x}_j$ are k nearest neighbors of each other with different class labels; otherwise, $s_{ij}^{(b)} = 0$. Thus, $\mathbf{S}_b$, $\mathbf{D}_b$, and $\mathbf{L}_b$ are obtained. The objective of MFA is to obtain the optimal projection vector $\mathbf{p}*$ such that

$$\mathrm{p}^* = \underset{\mathrm{p}}{\mathrm{argmin}} \frac{\mathrm{p}^T X L_w X^T \mathrm{p}}{\mathrm{p}^T X L_b X^T \mathrm{p}}$$

Here, the optimal $\mathbf{p}*$ is used as the basis for discriminative mapping of the facial makeup patterns after patch selection.

5. CONCLUSIONS

We have studied the problem of face detection and recognition based on the knowledge of how to apply cosmetics and various makeup foundations. We have explored four categorized of features facial skin tone, smoothness, highlight, and texture and then computed this all features in local patches of face images. We presented patch selection and discriminative mapping scheme proves to be essential in improving the accuracies of makeup detection effectively. The correlation mapping can be applied to the classified makeup or non-makeup without human intervention. Finally, we have presented a complete system that can perform automated face verification utilizing the makeup detection result.

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REFERENCES

1] P. Private, *et al.*, (2011, May). *How to Apply Makeup*. Available: http://www.wikihow.com/Apply-Makeup.
[2] T. Ahonen, A. Hadid, and M. Pietikainen, "Face recognition with local binary patterns," in *Proc. Eur. Conf. Comput. Vision*, 2004, pp. 469–481.
[3] C. Chen, A. Dantcheva, and A. Ross, "Automatic facial makeup detection with application in face recognition," in *Proc. ICB*, Jun. 2013, pp. 1–8.
[4] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *Proc. IEEE Conf. Comput. Vision Pattern Recognit.*, 2005, pp. 886–893.
[5] 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.
[6] 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.
[7] 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.
[8] R. Rosipal, "Nonlinear partial least squares: An overview," in *Chemoinformatics and Advanced Machine Learning Perspectives:* H. Lodhi and Y. Yamanishi, Eds. IGI Global, Hershey, PA, USA, 2011, pp. 169–189.
[9] R. Rosipal and N. Kramer, "Overview and recent advances in partial least squares," in *Subspace, Latent Structure and Feature Selection Techniques*Eds. Berlin, Germany: Springer, 2006, pp. 34–51.
[10] W. Schwartz, H. Guo, and L. Davis, "A robust and scalable approach to face identification," in *Proc. ECCV*, Sep. 2010, pp. 476–489.
[11] S. Shafer, "Using color to separate reflection components," *Color Res. Appl.*, vol. 10, no. 4, pp. 210–218, 1985.
[12] A. Sharma and D. Jacobs, "Bypassing synthesis: PLS for face recognition with pose, low-resolution and sketch," in *Proc. CVPR*, 2011, pp. 593–600.
[13] 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.
[14] M. Turk and A. Pentland, "Eigenfaces for recognition," *J. Cognitive Neurosci.*, vol. 3, no. 1, pp. 71–86, 1991.
[15] S. Ueda and T. Koyama, "Influence of make-up on facial recognition," *Perception*, vol. 39, no. 2, p. 260, 2010.
[16] 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.
[17] 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.
[18] 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.
[19] 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.
[20] 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.

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