PCA Based Human Face Recognition with Improved Method for Distorted Images due to Facial Makeup

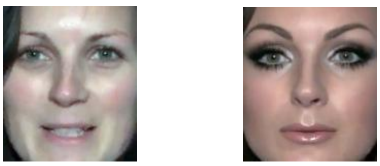
Bruce Poon, M. Ashraful Amin, and Hong Yan

Abstract — **Facial makeup may change the appearance of a face which can degrade the accuracy of an automatic face recognition system. Gradientfaces, an illumination invariant technique, has been found to work well with principle component analysis for human face recognition on images affected by illumination. Experiment results show that by applying the same technique, Gradientfaces, at the pre-processing stage which computes the orientation of the image gradients in each pixel of the face images and uses the computed face representation as an illumination invariant version of the input image, the recognition rates can be improved for a mixture of facial images with makeup and non-makeup. On the Youtube Makeup (YMU) Face database, we have achieved an increase of recognition accuracy from 76.25% to 84.50% in testing data which have images with makeup and non-make-up.**

Index Terms—**Face recognition, principle component analysis (PCA), gradientfaces, illumination insensitive measure, facial makeup.**

I. Introduction

FACIAL makeup is a cost effective and socially acceptable approach which could make a female appears more attractive and boost her sense of confident. However, facial makeup can change the perceived shape and texture of a face [1]. In Figure 1, it shows the effect of makeup on facial appearance. This effect could also severely affect the recognition performance of the current face recognition systems [1, 2]. In the past, a number of works had been done to solve that problem.



(a) (b)

Fig. 1 Sample images for a subject of the YMU Face Database : (a) without makeup and (b) with makeup

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II. Related Works

Ueda and Koyama [3] suggested that makeup may enhance or disguise facial characteristics. The influence of wearing makeup on facial recognition could be of two kinds: (i) when women do not wear makeup and then are seen with makeup, and (ii) when women wear makeup and then are seen without makeup. Their study is reported which shows that light makeup makes it easier to recognize a face while heavy makeup makes it difficult. Seeing initially a makeup face makes any subsequent facial recognition more difficult than initially seeing that face without makeup.

Scherbaum et al. [4] proposed a computer suggested facial makeup algorithm utilizing morphable face model [5] to find the best makeup for a given human face.

Dantcheva et al. [2] illustrated that non-permanent facial cosmetics can significantly change facial appearance, both locally and globally, by altering color, contrast and texture which in turn decreased in matching accuracy. They proposed the Local Gabor Binary Pattern (LGBP) [6] algorithm which could mitigate the effect of makeup on matching performance. Experimental results showed that LGBP outperformed other algorithms for face recognition on images with the presence of makeup.

Subsequently, Dantcheva et al. [7] proposed a SVM-based makeup detector in the context of face recognition. Output of the makeup detector was used to perform adaptive pre-processing. Experiment results indicated that by applying the proposed pre-processing routine, it could further improve the recognition accuracy of face matchers when matching makeup images against non-makeup images.

Eckert et al. [8] studied the impact of facial cosmetics on face recognition. The popular and efficient face recognition technique Local Binary Patterns (LBP) [9] is used for evaluation. Experimental results confirmed that the ability to identify a person's face decreased with increasing amount of makeup.

Han et al. [10] proposed the Histogram of Independent Component Pattern (HICP) in facial makeup effect. HICP is an unsupervised face representation learning technique that utilizes Independent Component Analysis (ICA) filter to process face images for representations that similar to those in human visual system. HICP encodes the computed ICA responses to binary pattern, congregates the regional histograms, regulates the high dimensional face representation and lastly compresses the representation for strengthened discriminability. The empirical results

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demonstrated that the proposed HICP was able to achieve on par with or even better recognition performance than other existing state of the art techniques.

The INface toolbox provided by Struc [11], [12] has a collection of various illumination normalization techniques. In our previous research work [13], we had identified that gradientfaces (GRF) based normalization technique [14] worked best with principle component analysis for human face recognition especially for those images affected by illumination.

Cosmetic effect has affected the recognition performance of the current face recognition systems including our PCA based human face recognition system. This paper presents the improved results on human face recognition utilizing gradientfaces (GRF) based normalization technique in the pre-processing stage for those images with makeup and without makeup. Details of works and experiments are described in the following sections.

III. Proposed Technique

A. *System Structure*

To handle facial recognition for those images with makeup and without makeup, Gradientfaces based normalization technique [14] is added in the pre-processing stage in order to compute the orientation of the image gradients in each pixel of the face images and uses the computed face representation as an illumination invariant version of the input image. A typical facial recognition system with four major generic components and an additional illumination normalization module, Gradientfaces, is shown in Figure 2.

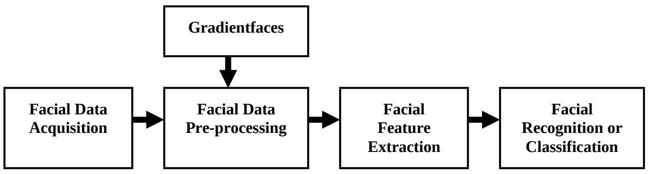

Fig. 2 A generic facial recognition system with illumination normalization

B. *Facial Image Acquisition*

Youtube Makeup (YMU) Face Database [15] is being utilized in this study. YMU is a publicly available makeup face database with 151 Caucasian female subjects. Each subject has 2 makeup images and 2 non-makeup images. Images are cropped, full frontal with bright illumination. Each image has 130x150 pixels.

The following three groups of face images have been selected from the Youtube Makeup Face Database:

a) Faces with non-makeup images; b) Faces with makeup images and c) Faces with a mixture of makeup and non-makeup images. Typical examples of various facial images are shown in Figures 3, 4 and 5.

Fig. 3 Sample images of the Youtube Makeup Face Database with non-makeup face images

Fig. 4 Sample images of the Youtube Makeup Face Database with makeup face images

Fig. 5 Sample images of the Youtube Makeup Face Database with a mixture of non-makeup (upper row) and their corresponding makeup face images (lower row)

C. *Facial Images Preprocessing*

In this preprocessing stage, we add the Gradientfaces based normalization technique [14] in order to extract the illumination insensitive measures which will be described as follow:

c.1 Reflectance Model: The reflectance Model used in many cases can be expressed as

$$I(x, y) = R(x, y)\, L(x, y) \tag{1}$$

where $I(x, y)$ is the image pixel value, $R(x, y)$ is the reflectance and $L(x, y)$ is the illuminance at each point (x, y). Here, the nature of $L(x, y)$ is determined by the lighting source, while $R(x, y)$ is determined by the characteristics of the surface of object. Therefore, $R(x, y)$ can be regarded as illumination insensitive measure. Separating the reflectance R and the illuminace L from real images is an ill-posed problem. In order to solve the problem, a "common" assumption is that L varies very slowly while R can change abruptly.

c.2 Gradientfaces: In order to extract illumination insensitive measure from gradient, we have the following

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theorem by studying the relationships between the components of gradient domain.

Theorem 1: Given an arbitrary image $I(x, y)$ taken illumination condition, the ratio of y-gradient of $I(x, y)$ ($\partial I(x, y)/\partial y$) to x-gradient of $I(x, y)$ ($\partial I(x, y)/\partial x$) is an illumination insensitive measure.

Proof: Considering two neighboring points (x, y) and $(x+\Delta x, y)$), according to the illumination model (1), we have

$$I(x, y) = R(x, y)\, L(x, y) \tag{2}$$

$$I(x+\Delta x, y) = R(x+\Delta x, y)\, L(x+\Delta x, y) \tag{3}$$

Subtracting (2) from (3), we obtain

$$I(x+\Delta x, y) - I(x, y) = R(x+\Delta x, y)\, L(x+\Delta x, y) - R(x, y)\, L(x, y)$$

Based on the above-mentioned "common" assumption, which means L is approximately smooth, we have

$$\begin{aligned} & I(x+\Delta x, y) - I(x, y) \\ & \approx R(x+\Delta x, y)\, L(x, y) - R(x, y)\, L(x, y) \\ & \approx (R(x+\Delta x, y) - R(x, y))\, L(x, y) \end{aligned} \tag{4}$$

Taking the limitation of the above equality (4), we can obtain

$$\frac{\partial I(x, y)}{\partial x} \approx L(x, y) \frac{\partial R(x, y)}{\partial x} \tag{5}$$

Similarly, we have

$$\frac{\partial I(x, y)}{\partial y} \approx L(x, y) \frac{\partial R(x, y)}{\partial y} \tag{6}$$

Dividing (6) by (5), we have

$$\frac{\dfrac{\partial I(x, y)}{\partial y}}{\dfrac{\partial I(x, y)}{\partial x}} \approx \frac{\dfrac{\partial R(x, y)}{\partial y}}{\dfrac{\partial R(x, y)}{\partial x}} \tag{7}$$

According to illumination model (1), R can be considered as an illumination insensitive measure. Thus, the ratio of y-gradient of $I(x, y)$ $\partial I(x, y)/\partial y$ to x-gradient of $I(x, y)$ $\partial I(x, y)/\partial x$ is also an illumination insensitive measure.

In practical application, the ratio of y-gradient of image to x-gradient of image might be infinitude derived by zero value of x-gradient of image. Therefore, it cannot be directly used as the illumination insensitive measure. These considerations lead us to defining Gradientfaces as follows.

Definition 1: I be an image under variable lighting conditions, then Gradientfaces *(G)* of image I can be defined as

$$G = \arctan\left(\frac{I_{y-gradient}}{I_{x-gradient}}\right), \quad G \in [0, 2\pi) \tag{8}$$

Where $I_{\text{x-gradient}}$ and $I_{\text{y-gradient}}$ are the gradient of image I in the x, y direction, respectively.

c.3 Implememtation: In order to extract Gradientfaces, we need firstly to calculate the gradient of face image in the x, y direction. Gradientfaces can then be computed by the definition (8). There are many methods for calculating the gradient of image. However, the numerical calculation of derivative (gradient) is typically ill-posed. To compute the gradient stably, we smoothen the image first with Gaussian kernel function. With a convolution-type smoothing, the numerical calculation of gradient is much more stable in calculation. The main advantage for using Gaussian kernel is twofold: (a) Gradientfaces is more robust to image noise and, (b) it can reduce the effect of shadows. The implementation of Gradientfaces can be summarized in Table I.

Table I Implementation of Gradientfaces

Input: Image I Output: The Gradientfaces of I 1. Smoothen input image by convolving with Gaussian kernel function: $I' = I * G(x, y, \sigma)$, where * is the convolution operator and $G(x, y, \sigma) = (1 / 2\pi \sigma^2) \exp(-(x^2 + y^2) / 2\sigma^2)$ is Gaussian kernel function with standard deviation σ. 2. Compute the gradient of image I by feeding the smoothed image though a convolution operation with the derivative of Gaussian kernel function in the x, y directions: $I_x = I' * G_x(x, y, \sigma)$, and $I_y = I' * G_y(x, y, \sigma)$, where $G_x(x, y, \sigma)$ and $G_y(x, y, \sigma)$ are the derivative of Gaussian kernel function in the x, y directions, respectively. 3. Compute the illumination insensitive measure by $G = \arctan(I_y / I_x) \in [0, 2\pi)$. 4. Obtain Gradientfaces $\leftarrow G$.

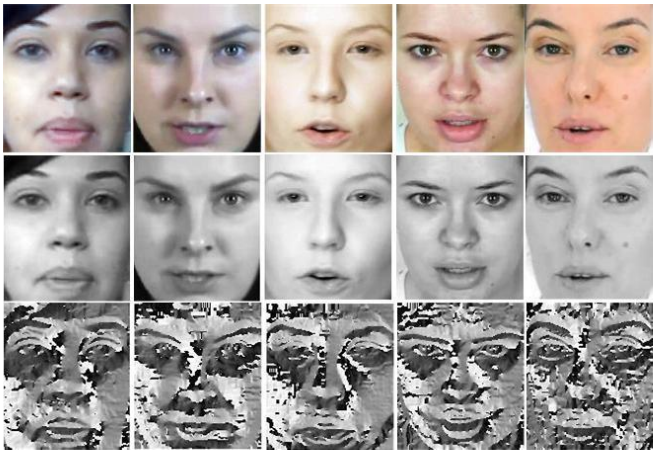

Fig. 6 Sample images of the Youtube Makeup Face Database with non-makeup face images (upper row), corresponding grayscale images (middle row) and the corresponding Gradientfaces processed images (lower row))

As Gradientfaces only works on grayscale images, color images are converted to grayscale images first before applying Gradientfaces. Figure 6 shows the non-makeup images, the grayscale images and the corresponding Gradientfaces processed images from the Youtube Makeup face database.

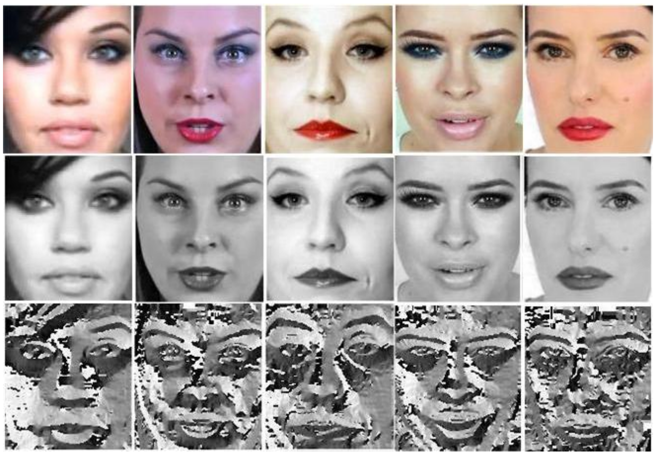

Fig. 7 Sample images of the Youtube Makeup Face Database with makeup face images (upper row), corresponding grayscale images (middle row) and the corresponding Gradientfaces processed images (lower row)

Figure 7 shows the makeup images, the grayscale images and the corresponding Gradientfaces processed images from the Youtube Makeup face database. Makeup can make facial images look sharper & brighter. However, Gradientfaces can extract the important illumination insensitive features of face, such as facial shapes and facial objects (e.g., eyes, noses, mouths, and eyebrows) which are key features for face recognition.

D. Facial Feature Extraction using principle component analysis (PCA)

Initial feature of a facial image is the gray intensity of each pixel. Each facial image is converted into a row vector by appending each row one after another. For the Youtube Makeup face database which has facial images geometry normalized and illumination insensitive measures extracted by the Gradientfaces technique has image size of 130 x 150. It will become a 19,500 dimensional feature vector which is very high for any classification technique to be applied in order to learn the underlying classification rules. Therefore, principle component analysis (PCA) is applied to extract more relevant features/signatures [16]. Principal component analysis (PCA) is a simple statistical method to reduce the dimensionality while minimizing mean squared reconstruction error [16].

Let us assume that M facial images that are denoted as $\mathrm{I}_1, \mathrm{I}_2, \ldots, \mathrm{I}_M$ have size $a \times b$ pixels. Using conventional row appending method, we convert each of the images into $N = a \times b$ dimensional column vector. At first the mean image as column vector, Ξ of size N, from all the image vectors of is calculated as:

$$\Xi = \frac{1}{M}\sum_{i=1}^{M} \mathrm{I}_i \qquad (9)$$

Then each face difference from the average is calculated using the equation (10).

$$a_i = \mathrm{I}_i - \Xi \qquad (10)$$

We then construct the matrix $A = [a_1, a_2, \ldots, a_M]$ containing all the mean-normalized face vectors as columns. Using this normalized face vectors we can calculate the covariance matrix $\Im$ along the feature dimension of size $N \times N$ of all the features using the following conventional formula as:

$$\Im = \frac{1}{N}\mathrm{AA}^T \qquad (11)$$

Notice that the matrix AA^T of size 19500×19500 needed to be constructed to calculate the matrix $\Im$. However, it is virtually impossible for the memory constrains to perform any matrix operation on the AA^T matrix. Rather, the method described in [17] is employed to construct the matrix $\aleph$ using Equation (12). Instead of AA^T, the matrix $\mathrm{A}^T\mathrm{A}$ is constructed as $\aleph$ of size $M \times M$ using:

$$\aleph = \frac{1}{M}\mathrm{A}^T\mathrm{A} \qquad (12)$$

Then we calculate the eigenvalue and eigenvectors of this covariance matrix using Equation (13).

$$[V, D] = eigs(\aleph) \qquad (13)$$

Here, $D = [d_1, d_2, \ldots, d_M]$ of size M contains the sorted eigenvalues, such that $d_1 > d_2 > \ldots > d_M$ and the corresponding eigenvectors of the matrix $\aleph$ is contained in the matrix $V = [v_1, v_2, \ldots, v_M]$ which is of size $M \times M$. According to the method proposed in [24], we can acquire the corresponding eigenvectors of the matrix $\Im$ using $V = [v_1, v_2, \ldots, v_M]$ as:

$$U = A \times V \qquad (14)$$

Here notice that, even though each vector v_i is of size M, the vectors u_i of $U = [u_1, u_2, \ldots, u_M]$ are of size N. We can use the matrix U to project our N data onto lower M dimensions. The projected data from the original N dimensional space to a subspace spanned by r principal eigenvectors (for the top r eigenvalues) contained in the matrix Ω_r expressed as:

$$Y_r = \Omega_r A \qquad (15)$$

In our previous research work [18, 19], we chose the top 50 principle components as features in the lower dimension as the sum of the top 50 eigenvalues of the covariance matrix is more than 90% of the sum of all the eigenvalues.

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E. Facial Recognition or Classification

When all the facial images are finally represented with relevant features by projecting onto a lower dimension using PCA, we can use similarity measures between faces from the same individual and different individuals. Assume that the normalized vector formed face test images are kept in the matrix, where each column corresponds to a test face image. For classification, we first normalize the test images vector by subtracting the mean calculated previously (Equation (9)) using:

$$B = T - \Xi \tag{16}$$

Then using Equation (15) we project the normalized test data set as shown in the following equation.

$$Z_r = \Omega_r B \tag{17}$$

For each column in the matrix Z_r, we calculate the Euclidean Norm of the difference with the projected vectors of matrix Y_r. Finally, the test image is identified as the person with the smallest value among all the Euclidean Norm values.

IV. Experiment Results And Discussion

Figures 8, 9 & 10 show the recognition accuracy with & without Gradientfaces preprocessing for Youtube Makeup Face Database with non-makeup images only, with makeup images only and with a mixture of non-makeup and makeup images.

In Figures 8 and 9, for face database with non-makeup or with makeup images only, addition of Gradientfaces in the pre-processing stage does not improve the accuracy as both PCA and PCA + Gradientfaces achieve up to 100% recognition rate.

In Figure 10, for face database with a mixture of non-makeup and makeup images, addition of Gradientfaces in the pre-processing stage improves the recognition rate, from 76.25% to 84.50%.

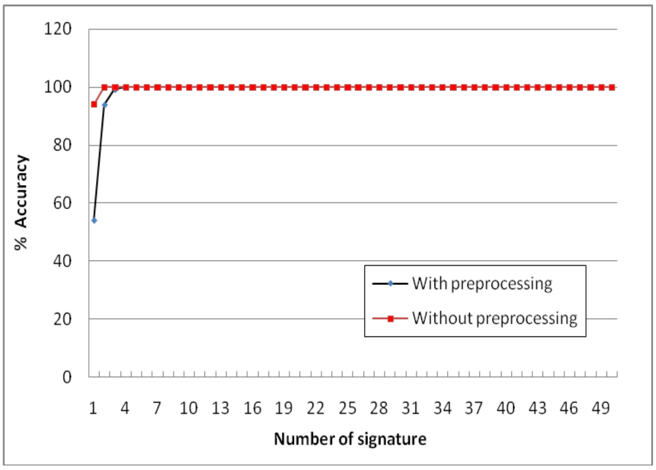

Fig. 8 Recognition accuracy with and without Gradientfaces preprocessing for the Youtube Makeup Face Database with non-makeup face images

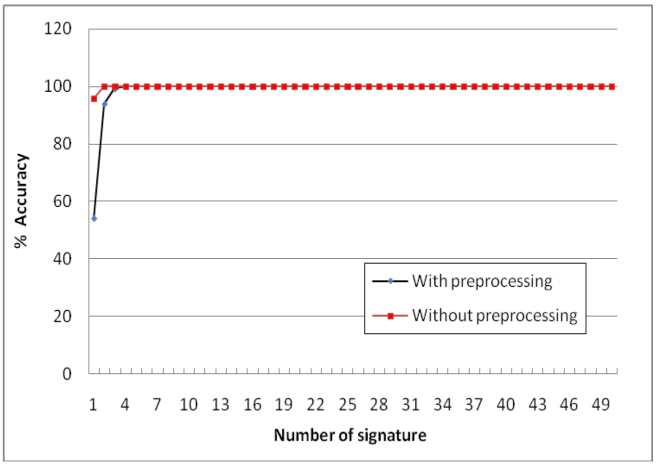

Fig. 9 Recognition accuracy with and without Gradientfaces preprocessing for the Youtube Makeup Face Database with makeup face images

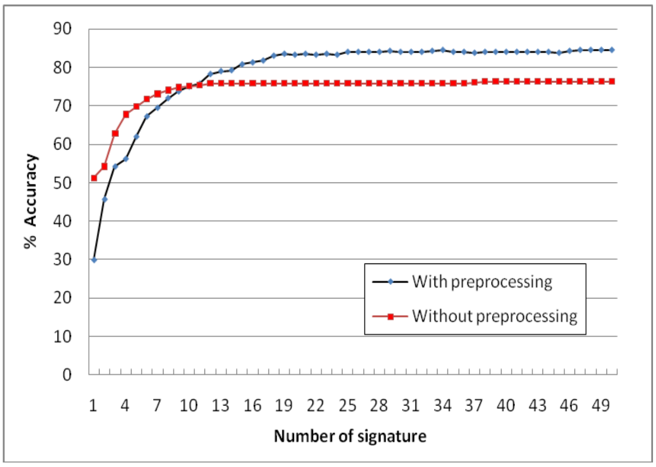

Fig. 10 Recognition accuracy with and without Gradientfaces preprocessing for the Youtube Makeup Face Database with a mixture of non-makeup and makeup face images

The results are summarized in Table II.

Table II Summary of testing results for Youtube Makeup Face Database

Conditions	Recognition accuracy without preprocessing	Recognition accuracy with Gradientfaces for preprocessing	% of improvement
Non-makeup images	100%	100%	0%
Makeup images	100%	100%	0%
Mixture of non-makeup and makeup images	76.25%	84.50%	10.82%

V. Conclusions

Facial makeup changes the appearance of a face which affects the recognition accuracy of our PCA based human face recognition. With illumination normalization technique in the facial image preprocessing stage to extract the illumination invariant features, it improves the recognition rate, from 76.25% to 84.50%.

Apart from facial images with makeup, distorted images also include noisy & blurry images. With the characteristic of Gradientfaces normalization technique, further research works will be done on those noisy & blurry facial images if this Gradientfaces can also work well with our PCA based human face recognition system.

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