FACE RECOGNITION USING GENDER INFORMATION

Wonjun Hwang[1], Haibing Ren[1], Hyunwoo Kim[2], Seok-Cheol Kee[3], Junmo Kim[4]

{wj.hwang, haibing.ren}@samsung.com, hwkim@kgit.ac.kr, sckee@robotever.com, junmo@ee.kaist.ac.kr
[1] Samsung Electronics, Korea, [2] KGIT, Korea, [3] Robotever Inc., Korea, [4] KAIST, Korea

ABSTRACT

In this paper, we propose a novel method using gender information for achieving better performances of face recognition systems. Gender is one of the important factors for recognizing appearance of human faces and there are many studies on gender classifications such as [1]. However, the gender information is not actively applied in vision-based face recognition tasks, because we cannot find out human identity using only gender information. Therefore, we design the face recognition system based on the gender-based facial features with global facial features, and moreover, gender-based score normalization method for verification task. For fair evaluations, we use FRGC database known as a large size face image database.

Index Terms— Face Recognition, PCA, LDA, Gender Information, Score Normalization

1. INTRODUCTION

When people recognize human faces, the visual information of faces plays a pivotal role. It is largely because the visual information is more familiar and intuitive to people than other clues. We can divide such visual information into two different kinds of components for facial recognition, to be specific, fundamental and supplemental facial components. At first, the fundamental facial component is the human face's unique characteristic, for example, two eyes, a nose and a mouth. The different shape, size and position of the fundamental facial component are used in a basic face detection and recognition. On the other hand, the supplemental facial components could be used to cluster face images according to biological roles such as genders, races and age groups. Supplemental elements could contribute to reducing the candidates of identities during a recognition procedure.

In the field of computer vision, many researchers have studied statistical learning methods for face recognition. For example, Principal Component Analysis (PCA) [2] and Linear Discriminant Analysis (LDA) [3] have attracted attention of researchers due to their simplicity and performances. In particular, LDA has shown the good accuracy for the expected variations learned in the training stage. However, they do not directly utilize supplemental facial components for face recognition and simply rely on the learning theory based on the statistical observations of training samples. If the training data set is representing various groups of people, for instance male group and female group or a variety of ethnic groups, in balanced way, these methods based on fundamental facial components would perform well enough. However, oftentimes data sets are not well-balanced. For example, from the aspect of the gender information, which is one of the representative supplemental facial components, the image number ratio between the male and the female data is not equal in common training images. In particular, the number of female samples is often smaller than that of male samples. It means that the generated face model could be biased to the specific gender.

In this paper, we have employed the gender information in face recognition for performance improvements. The reason why we adopted the gender information among many supplemental components is that we can have only two clusters by human gender, and moreover, recently the gender has attracted attention in psychological field [4]. To achieve this work, we fundamentally assume the gender classification was done correctly in advance. We propose the salient facial features which are extracted by a global face model and gender-based face models. The gender-based score normalization scheme is also designed as one of post-procedures for the verification accuracy. In case of face models, we construct two different gender-based face models – female model and male face model, respectively, because male and female face images have the dissimilar property as shown in Fig. 1, which is caused by interior (ex. different shapes and sizes of skulls according to genders) and exterior (ex. appearance changes by makeup and hair style) differences. Since man's face appearances are more various and most of training sets have smaller female images than male, when you built a global face model with the whole training set, you could lose the chance to use the female gender's characteristics in face recognition. FRVT 2002 document [5] reported that the accuracy for female faces is 6%~9% worse than that of male faces. Therefore, we employ both a global face model and a gender-based face model to compensate for the performance reduction at the specific gender. In addition, the gender-based score normalization scheme is adopted as a post-processing for boosting the verification accuracy. If genders between a query and a target are not the same, we set the similarity value into the lowest point. We then calculate parameters of the score normalization with the similarity values of the same gender.

The rest of this paper is organized as follows: proposed method to use gender information for recognition is described in Section 2, and the experimental results and discussions are given in Section 3. At last, the conclusion is summarized in Section 4.

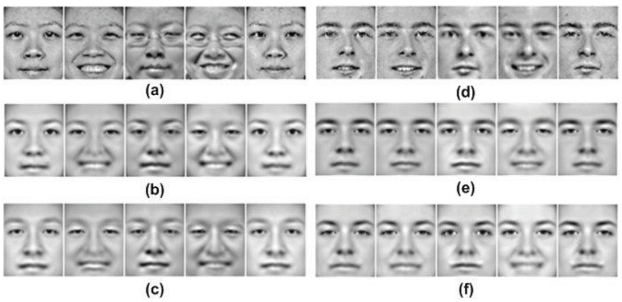

Fig. 1. (a) and (d) are original face images, (b) and (e) shows reconstructed images after projection to correct gender face models by PCA. On the contrary, (c) and (f) are reconstructed images by different gender face models, and some images look like different gender's appearances against the original images in comparison with (b) and (e) images.

2. GENDER INFORMATION FOR FACE RECOGNITION

2.1. Linear Discriminant Analysis

LDA [3] is a popular supervised learning method to find proper linear projections in subspaces that maximize the between-class scatter while minimizing the within-class scatter of the projected data. For this purpose, two scatter matrices – the between-class scatter matrix $\mathbf{S}_B$ and the within-class scatters matrices $\mathbf{S}_W$ – are defined with an input image vector $\boldsymbol{\chi}$ as

$$\mathbf{S}_B = \sum_{i=1}^{c} M_i(\mathbf{m}_i - \mathbf{m})(\mathbf{m}_i - \mathbf{m})^T \ , \quad (1)$$

$$\mathbf{S}_W = \sum_{i=1}^{c} \sum_{\chi_k \in c_i} (\boldsymbol{\chi}_k - \mathbf{m}_i)(\boldsymbol{\chi}_k - \mathbf{m}_i)^T \ , \quad (2)$$

where $\mathbf{m}$ is the global mean vector of face images and $\mathbf{m}_i$ is the mean image vector of i th class, c_i, which has $\mathbf{M}_i$ samples. c is the total number of classes. The transformation matrix, $\mathbf{W}_{opt}$, is formulated as

$$\mathbf{W}_{opt} = \arg\max_{\mathbf{W}} \frac{|\mathbf{W}^T\mathbf{S}_B\mathbf{W}|}{|\mathbf{W}^T\mathbf{S}_W\mathbf{W}|}. \quad (3)$$

In general, PCA firstly reduces the vector dimensionality before performing LDA to overcome the singularity of within-class scatter matrix.

$$\mathbf{y} = (\boldsymbol{\Phi}\mathbf{W}_{opt})^T(\boldsymbol{\chi} - \mathbf{m}) = \mathbf{U}^T(\boldsymbol{\chi} - \mathbf{m}) \ , \quad (4)$$

where $\boldsymbol{\Phi}$ is the matrix of eigenvectors and $\mathbf{y}$ is a extracted facial feature vector.

2.2. Global and Gender-based Linear Discriminant Face Model

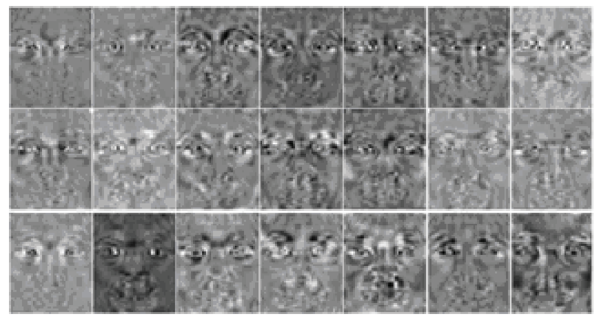

Fig. 2. First row images are basis sample images of a global face model, and second and third row shows the basis images of a male face model and a female face model, respectively.

Before using gender information for recognition, we assume that the gender classification has been done correctly. At first, we can learn a global face model with a whole training facial image set G by Equation (3), and two gender-based face models can be made on the basis of each gender characteristic, too. We divide the whole training sets G into female set F and male training set M so that $G = M \cup F$. With female and male training sets F and M, we can make additional two gender-based face models, respectively. Three discriminant transformation matrices, $\mathbf{U}_G$, $\mathbf{U}_F$, and $\mathbf{U}_M$, are finally constructed by LDA. Fig. 2 shows their example basis images of three discriminant transformation matrices, and they are not similar to one another. From Fig. 1 and Fig. 2, we can know female and male faces have some mutual exclusive features, and they could not be properly covered by the global face model by itself. Therefore, the gender-based face models made by artificial classifications are necessary for the compensation.

After learning three face models, it is the problem how to use these models effectively. The easiest way is using only single gender-based face model relevant to an input image, but in this paper, we propose the concatenated model that consists of the global and the gender-based models for achieving better performance. The global face model basically plays a principal role in recognition, and moreover, the other, the selected gender-based face model, can be used as complementary features [6]. In detail, the elements of $\mathbf{y}_s$ have coefficients extracted by the global face model, and those of $\mathbf{y}_s$ have coefficients extracted by each gender-based face model. It is not reasonable to compare them directly due to different means and variations. To compensate this challenge, we should estimate the effect of varying $\mathbf{y}_s$ on the sample images.

$$\mathbf{y}_s^{'} = \begin{pmatrix} \mathbf{y}_G \\ \mathbf{D}_s \mathbf{y}_s \end{pmatrix} = \begin{pmatrix} \mathbf{U}_G^T(\chi - \overline{\mathbf{m}}_G) \\ \mathbf{D}_s \mathbf{U}_s^T(\chi - \overline{\mathbf{m}}_s) \end{pmatrix}, \quad (5)$$

$s \in \{F, M\}$, $\mathbf{D}_s = r \cdot \mathbf{I}$ where r^2 is the ratio of the total global feature variation to each gender feature variation.

With this concatenated features, similarity between query and target images can be measured by normalization correlation.

$$S(\mathbf{y}_q^{'}, \mathbf{y}_t^{'}) = \frac{\mathbf{y}_q^{'T} \mathbf{y}_t^{'}}{\| \mathbf{y}_q^{'} \| \cdot \| \mathbf{y}_t^{'} \|} \quad (6)$$

2.3. Gender based Score Normalization

Begin initialize
  i ← 0
  do i ← i + 1
    ith score vector is
    $\mathbf{Z}_i = \left[S_1(\mathbf{y}_{q_i}^{'}, \mathbf{y}_{t_1}^{'}) \quad S_2(\mathbf{y}_{q_i}^{'}, \mathbf{y}_{t_2}^{'}) \quad \cdots \quad S_N(\mathbf{y}_{q_i}^{'}, \mathbf{y}_{t_N}^{'}) \right]$
    Calculate a mean and a variance of the Z_i row in case of query's gender=targets' gender
    $m_s = \frac{1}{n_g} \sum_{i=1, g_q = g_t}^{n_g} S_i \qquad \sigma^2 = \frac{1}{n_g} \sum_{i=1, g_q = g_t}^{n_g} (S_i - m_g)^2$
    if $g_q = g_t$
      $S_j^{'}(y_g, y_{t_j}) = \frac{S_i(y_g, y_{t_j}) - m_g}{\sigma_g}$
    else
      $s_j^{'}(y_g, y_{t_j})$ = The lowest score value
  until i = M
end

Fig. 3. Pseudo code of gender-based score normalization.

In a verification task, score normalization scheme can be used as the post-processing to increase the performance of verification measures such as False Rejection Rate (FRR), False Acceptance Rate (FAR), and Equal Error Rate (EER) [9]. In contrast, the score normalization does not change the order of retrieved images and cannot help to increase retrieval and identification accuracy.

The popular score normalization method is the z-score normalization [8], but in this paper we calculate the parameters from similarity values when targets' genders are identical to the query. The whole procedure of the proposed score normalization is described in Fig. 3.

3. EXPERIMENTAL RESULTS AND DISCUSSION

Fig. 4. Example images of FRGC database are shown. In four images, the first two are controlled images and others are uncontrolled images.

Table 1. Average performances of global, genders and the proposed models without score normalization scheme.

Test Set	Train Variation	EER	VR (0.1%)	CMC (1^{st})
Male Test Set	Global Model	7.53%	53.66%	47.61%
	Male Model	8.08%	52.13%	47.15%
	Female Model	15.09%	15.41%	13.87%
	Proposed Face Model	7.34%	55.47%	50.24%
Female Test Set	Global Model	8.81%	34.03%	46.41%
	Male Model	14.03%	16.52%	22.33%
	Female Model	8.71%	38.61%	45.83%
	Proposed Face Model	8.06%	38.08%	50.90%

Table 2. Average performances of each algorithm in total test sets

Method	EER	VR(0.1%)	CMC(1^{st})
Global Face Model	6.68%	46.99%	49.39%
Global Face Model + Z-Score Normalization	5.95%	59.54%	49.39%
Proposed Method	4.51%	64.93%	54.29%

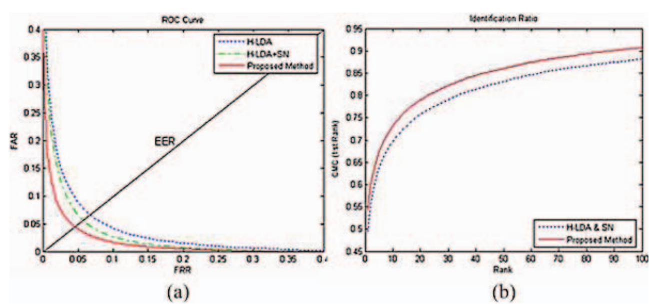

Fig. 5. (a) Verification and (b) identification accuracies

For the performance evaluations, Face Recognition Grand Challenge (FRGC) ver 2.0 [7] sets has been used. It provided the training set and several test protocols. The training set consists of 12,776 images with 222 individuals (130 males and 92 females) and the test set consists of 16,028 controlled images and 8,014 uncontrolled images (265 males and 201 females). The controlled images were taken under studio lighting with two facial expressions, and the uncontrolled images were taken in varying illumination conditions (e.g., hallways, atria, or outdoors). In this paper, controlled and uncontrolled images were used as the target set and the query set, respectively, which is similar to Experiment 4 protocol of FRGC. Each set were divided into four subsets for convenience. All total accuracies were always measured by the average of four trials. For measurements of performances, Verification Rate (=1-FRR) at FAR = 0.1%, EER, and Cumulative Match Characteristic (CMC) Curve [9] at 1st rank are employed. Face images are normalized with manual eye positions into 46 × 56 image sizes, as shown in Fig. 4. In this experiment, we do not employ any preprocessing for the illumination compensation such as histogram equalization.

Table 1 shows that the female face recognition is generally more difficult than that of the male face, especially in a verification task. The reasons of the better performance of males than females' in the global face model are that (1) the number of male training samples is basically larger than female images (130>92), and (2) female faces are more similar to the average face, so that woman's between discriminant power is weaker than man's. In addition, (3) female within variation is more complex because of daily changed makeup, hair style, accessory and etc.

Another interesting thing is that different gender training model cannot span the other, for example, male trained model achieved 52.13% VR in male test set, but only 15.41% in female test set at the same time. This tendency is similar in a female model. On the other hand, the proposed concatenated face models make sure of better performances than the global model and the gender-based face model. For example, it shows 50.90% CMC in comparison with global model, 46.41%, and female model, 45.83%, in the female test protocol. Consequently, though the dimensionality of a feature vector is increased by a complementary face model, the accuracy of the overall face recognition is increased.

Performance comparisons in total test sets are shown in Table 2 and Figure 5. The proposed method which consists of the proposed concatenated face model and the gender-based face score normalization achieves the best accuracy in both verification (VR) and identification (CMC) measures. As shown in Table 2, Verification rate is increased from 59.45% to 64.93% and identification rate is also improved from 49.39% to 54.29% by the proposed face models.

In this respect, we conclude the gender-based face models could be used as complementary features with the global face model for better stability and accuracy of recognition.

4. CONCLUSION AND FUTURE WORK

We propose salient features which consist of global features and gender based features. To extract a facial descriptor from a face image for the face-based image retrieval system, we adopt two different features, so that we can boost performance in comparison with that of a single feature. Moreover, the gender-based score normalization is also proposed for verification accuracy. In this frame work, we can make use of human gender information properly for recognition.

To apply another supplemental facial component in face recognition, we will study on how to use ethnical information [10] in the future. Learning face models using ethnical information is also important, because different races have different variations in face images.

11. REFERENCES

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