Component-based Gender Classification based on Hair and Facial Geometry Features

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Abstract: In this paper, a component-based gender classification based on hair and facial geometrical features are presented. By way of these preprocessing, hair and facial geometry features can then be extracted automatically from the face images. We compare hair detection methods by examining their color and texture features, and also analyze some geometrical features from references. The best performance of 87.15% in gender classification rate is achieved by combining the most significant hair and geometrical features which is better than some of the literature before.

1 INTRODUCTION

Gender classification is a branch of face recognition that can be used as pre-treatment or in combination with other identification to improve recognition results. In addition, the human face recognition technology can be used not only for identity recognition, but also the images and related multimedia interaction applications. According to biology, human being can distinguish gender difference by seeing face regions. After choosing the general direction, there are still two main approaches for face gender classification: appearance-based and feature-based (Makinen and Raisamo, 2008). The appearance-based approach takes advantage of full image, in which all pixels are counted for its result to analyze. The feature-based is according to facial organ or special region's characters, like the measure of area, length and width, distance, position, relative position and so on. Many correlative introductions about these two main approaches are also found in some articles. Since the appearance-based approach must handle all pixels for a given images, it will lower down the recognition performance. Therefore, in this paper we just pay attention to the component-based method. We will introduce the hair and facial geometry features detection of the literature as follows.

2 THE PROPOSED GENDER CLASSIFICATION

The architecture of gender classification system is presented in Fig. 1. The system can be roughly divided into three modules, which are preprocessing module, feature extraction module and classification/recognition module. We will introduce the content one after another.

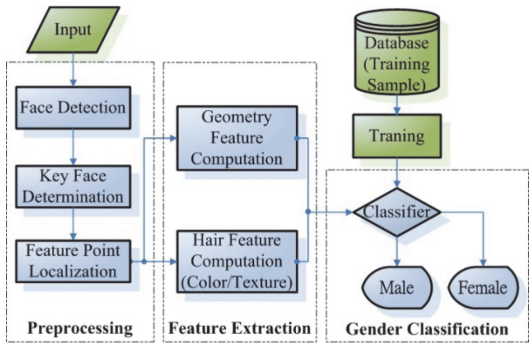

Figure 1: Architecture of gender classification system.

2.1 Pre-processing

We can count the weights of each face in an image based on the formula, then follow the weight size to recognize the key face in the image to get its information. Then, for the purpose of feature-based computation, many feature regions are computed

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individually. The computed regions and the remained steps are shown in Fig. 2. The most important issue to be solved in this premise is to find out the position precisely of face organ characters. So this work uses ASM (Active Shape Model) (Lanitis et al., 1995) to locate the feature points and to find the special region's characteristics.

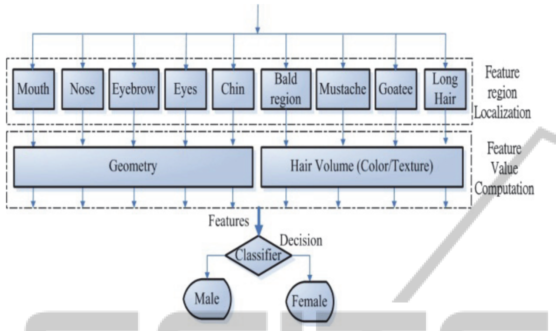

Figure 2: Flowchart of face localization, feature extraction and recognition.

2.2 Hair Detection

In previous sections, two kinds of hair detection methods are discussed. We use these two methods to compute the special regions' hair volume to find the gender uniqueness. The effective zones of hair features are shown in Fig. 3.

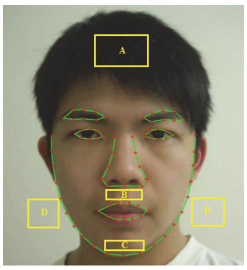

Figure 3: (a) Bald region, (b) mustache, (c) goatee, and (d) long hair.

2.2.1 Adaptive Skin and Hair Color Detection

Adaptive detection technique uses the detection regions which are similar to target test color areas. Thus it can reduce the skin and hair color influenced by ethnic.

As shown in Fig. 4, for getting the hair feature, we should extract the skin (cheek) color without glasses and hair interference, and remove all the skin color from image first. Then, we use the hair color region with no skin color for extracting hair from the image. That is fundamental for hair region detection. By the way, if the system determines that the forehead region is completely bald, then the extraction is from the right eyebrow. Detail of the hair extraction process is shown in Fig. 5.

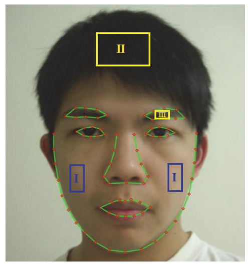

Figure 4: Region (I): Skin color extraction. Regions (II) and (III): Hair color extraction.

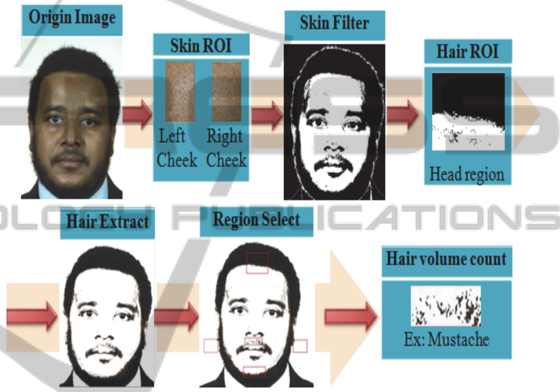

Figure 5: The procedure of hair color extraction.

Skin color distribution of course is based on YCbCr color space to calculate mean value and standard deviation, like Eqs. (1) and (2). Then it determines up and down threshold of skin color based on mean value and standard deviation, like Eqs. (3) and (4). Then according to Eq. (5), it classifies if every pixel is skin color. As the same way, hair color extraction also uses this algorithm to complete hair region volume. The computation is as follows.

$$\mu_{(Y,Cb,Cr)} = \frac{1}{n}\sum_{P_{i,j}\in ROI_1} P_{i,j} \quad (1)$$

where $\forall P = [Y, Cb, Cr]$, and $\mu_{(Y,Cb,Cr)} = [\mu_Y, \mu_{Cb}, \mu_{Cr}]$

$$\sigma_{(Y,Cb,Cr)} = \frac{1}{n}\left\{\sum_{P_{i,j}\in ROI_1}\left[P_{i,j} - \mu_{(Y,Cb,Cr)}\right]^2\right\}^{\frac{1}{2}} \quad (2)$$

where $\forall P = [Y, Cb, Cr]$, and $\sigma_{(Y,Cb,Cr)} = [\sigma_Y, \sigma_{Cb}, \sigma_{Cr}]$

$$H_U = \mu_{(Y,Cb,Cr)} + 3\sigma_{(Y,Cb,Cr)} \quad (3)$$

$$H_L = \mu_{(Y,Cb,Cr)} - 3\sigma_{(Y,Cb,Cr)} \tag{4}$$

$$\begin{cases} 1 & H_L < I_{x,y} < H_U \\ 0 & \text{Other} \end{cases} \tag{5}$$

ROI_1 is the skin color sampling area, ROI_2 is the total face including hair scope.

$P_{i,j}$ is the distribution of all pixels of ROI_1, $i = 1,2,\cdots,N_1$, $j = 1,2,\cdots,M_1$

n is the total pixel number of ROI_1, $n = N_1 * M_1$

$I_{x,y}$ is the distribution of all pixels of ROI_2, $x = 1,2,\cdots,N_2$, $y = 1,2,\cdots,M_2$

2.2.2 Gabor Transform for Hair Texture Detection

Among many of texture detection methods, Gabor transform has the excellent performance (Manjunath and Ma, 1996). So we used Gabor wavelet to convert an image to magnitude response. Still, as Fig. 6, if we change the light environment of image, texture information may have higher beneficial detection result (Maenpaa, 2004). We enhance the light and contrast before transferring. Detail process of the hair extraction is shown in Fig. 7.

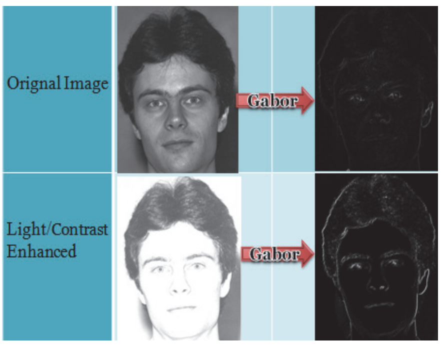

Figure 6: Environment lighting example.

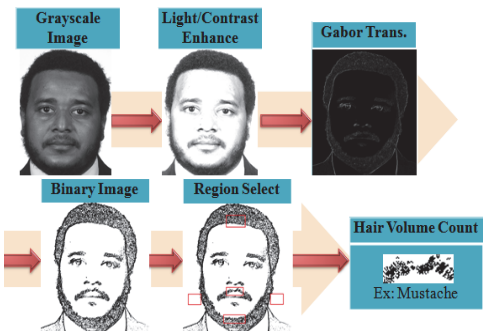

Figure 7: The procedure of hair texture extraction.

The general idea of Gabor transform is shown in Fig. 8. Gabor filter can be separated into real, imaginary and magnitude responses from Eq. (6), we just pick out the magnitude feature for texture detection from Eq. (7). Gabor magnitude transform is to make Gabor filter convolution with image f and then observe the change of texture from Eq. (8). The parameters of the filter used here are $\psi = \sqrt{2} \quad \theta = 0^\circ \quad \sigma = 0.2 \times PI$.

$$\begin{aligned} G_{\text{¿},}(x,y) &= g_\sigma(x,y) \times \exp\left(j2\pi\text{¿}\left(x\cos \ + y\sin \ \right)\right) \\ &= G_R(x,y) + jG_I(x,y) \end{aligned} \tag{6}$$

$$g_\sigma(x,y) = \frac{1}{2\pi\sigma^2} \times \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) = \sqrt{\left[G_R(x,y)\right]^2 + \left[G_I(x,y)\right]^2} \tag{7}$$

$$G(x,y) = \sum_i \sum_j f(x+i, y+j) \otimes g_\sigma(x,y) \tag{8}$$

$G_{\text{¿},}(x,y)$ is Gabor filter.

¿ : frequency θ: orientation σ: bandwidth

$G_R(x,y)$, $G_I(x,y)$ and $g_\sigma(x,y)$ are real, imaginary, and magnitude responses of Gabor filter.

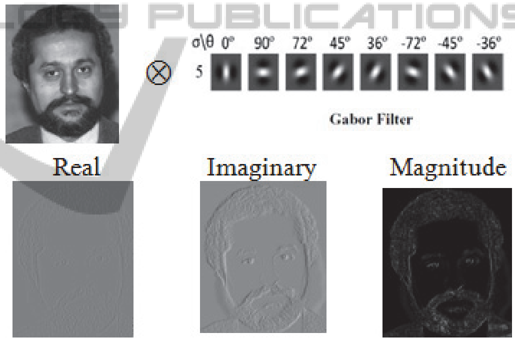

Figure 8: Gabor transform.

2.3 Computation of Geometrical Features

In the case of geometry length measurement, it calculates all the statement Euclidean distances between the selected points on a face in Fig. 9. This article compares those proposals in the literature from the group of geometric and cross combination, to find the most recognizable geometry length (A. Samal et. al's feature lengths are in the name of Samal). To decrease the variation of distance from object and reduce the complication of full image normalization, we normalized each fine line's values from the thick line's distance between two eyes.

Table 1: Comparison of individual feature and classification.

	Samal	Internal	External	Pogonion	Vertical	Right Side	Hair texture	Hair color
SVM	**67.85%**	**65.05%**	**66.70%**	**65.85%**	**62.85%**	**65.40%**	**80.10%**	**72.65%**
Modest AdaBoost	**65.30%**	**62.10%**	**61.35%**	**65.15%**	**62.00%**	**64.65%**	**79.25%**	**70.05%**
LogitBoost	**64.60%**	**60.70%**	**60.65%**	**64.75%**	**61.75%**	**64.30%**	**78.30%**	**66.35%**
Real AdaBoost	**64.65%**	**60.30%**	**59.55%**	**65.00%**	**61.45%**	**64.10%**	**78.55%**	**66.85%**

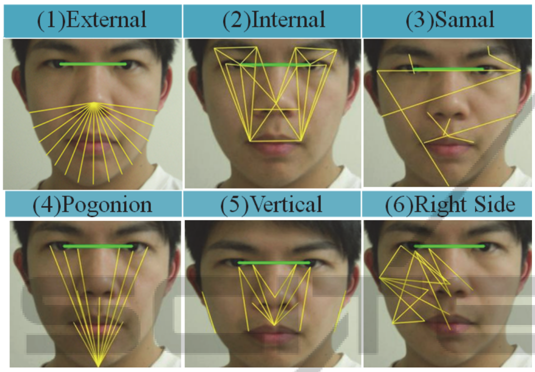

Figure 9: Geometrical feature extraction (thick line for normalization).

3 EXPERIMENTAL RESULTS

3.1 Database

Related to face recognition scope, FERET database is an image database extensively used. There are 14,126 pictures in the database, including 1,199 persons and about 2,722 images. We choose 2,000 images (male and female have 1,000 images, respectively) to test colorful face images.

3.2 Experimental Results

At first, we compare all the classifiers and individual features as shown in Table 1. For all listed classifiers, SVM has the best performance than the others. And if focusing on individual feature, the result shows that hair features get higher correct classification rate than geometry features, we can consider it as strong features. But for individual feature, there is still betterment.

Moreover, For the purpose of getting higher correct classification rate, we had tested many sets of feature combination. I just list some well performed results as shown in Table 2. For facial geometry gender classification, combined with Samal and external feature it has the best performance. From this, we can understand that it is not always the case that the more geometry features selected, the better performance it will be. Still more, if it can combine strong feature of texture detection, the total correct recognition rate can be higher up to 87.15%.

Table 2: Performance of feature combination.

Texture	(1) complex background, (2) wrinkle and pores (3) susceptibility to light.
Color	(1) darkness background, (2) region selected (3) the same color as skin, (4) susceptibility to light.

Table 3: Performance of combined features.

Feature Combination	**Features**	**Rate**
Internal + External	39	69.00%
Samal+ External	25	70.10%
Pogonion + External	29	69.85%
Samal + External + Hair color	29	79.55%
Samal + External + Hair texture	29	87.15%
Samal + External + Hair texture and color	33	86.55%

3.3 Discussion

There are more changing factors of color features than the texture features, so it is easy to know the poor results that should be. The normal color and texture influence factor are shown as Table 3. As you can see, even system can achieve the best performance from simulation results, texture features is not always better than color features for long hair detection, even though texture features can get the best recognition rate in experiments. The reason is that FERET has many pictures in simple background, and just changes the influence of light. In practice, we should choose the features combination methods that rely on the changes of back ground or to eliminate background.

4 CONCLUSIONS

In this paper, we construct a fast and low complex gender classification system. Our experimental results show the importance of hair texture and the most appropriate geometry characteristics of matching for gender classification. We can still find the importance of texture features, because of color causes more unpredictable factors. Finally, the best performance of our proposed system is to combine hair and geometry features that can get the classification rate to 87.15% in gender classification.

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