GENDER CLASSIFICATION USING NECK FEATURES EXTRACTED FROM PROFILE IMAGES

By

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ABSTRACT

Gender classification has been one of the emerging issues in the field of security due to increase of women-only floors. For security purpose, this paper presents two Biological Features extracted from the Neck Region in a Profile Image. One has extracted the bump of the neck formed by the laryngeal prominence. Another is the width of the neck that tends to be wider in males than in females. Evaluation experiments for the proposed two features were performed on 50 male and 39 female profile images. The experimental result shows that the proposed method achieved over 95.0% accuracy for both of the male and female images, which overcomes a state-of-the-art method based on Local Binary Patterns for gender classification.

Keywords: Gender Classification, Profile Image, Neck Feature.

INTRODUCTION

A wide variety of applications for gender classification has been developed in various fields [3]. A typical example of gender classification is market analysis. In environments such as supermarkets and convenience stores, it is important to recognize the gender and age of customers for making good sales strategies. Nowadays, POS (Point Of Sales) system is used to gain customer attributions such as gender, age, and ethnicity and they are input manually. However, there exist two major problems in POS system. First, customer attributions are determined in a subjective manner. Second, it requires human hand to input customer's attribution. In recent years, gender classification has also been required for security purpose. Women-only floors are provided in several hotels and key cards are used to control the user's entrance and exit. However, a man would get into the floor by receiving the key card from a woman, or picking up a lost key.

Existing methods for gender classification have been broadly divided into two categories, namely appearance-based approach and geometric-based approach. Appearance-based approach refers to dynamic features such as clothing, hairstyle, voice, and gait [1,6,8,10]. Since this approach is based on the perception of the human, the dynamic features above enable a powerful performance on gender classification. Geometric-based approach measures distances of pixels between facial parts such as nose, mouse, and eyes [11]. Nowadays, combination of both approaches have been actively proposed [2,9]. As another major approach on gender classification, [4] proposed a method for employing LBP (Local Binary Patterns) to facial images. In addition, [7] proposed an improved version of LBP called SLBM.

This paper focuses on gender classification for security purpose. Currently, most existing methods using image analysis are basically designed to apply to frontal face images. However, it has been reported that criminals often conceal their face from security cameras. Hence, methods for gender classification specialized for security purposes have been required.

In order to classify the gender for security purpose, this paper presents two biological features extracted from profile images. Compared with frontal images, the profile images have significantly fewer characteristics. By observing profile images, we can see that the dump formed by the laryngeal prominence is larger in males, while in females it is usually visible. Considering this characteristic, this paper presents a feature extracted from the bump. Besides, the proposed method calculates the width of the neck as another feature for gender classification. Since both of the features are extracted from neck region, the proposed method still works in situation when a man disguises himself as a woman or conceals his face. Evaluation experiments for the proposed features show a powerful performance in gender classification.

The rest of this paper is organized as follows. First, the authors describe the way of extracting the proposed features in section 1. In section 2, evaluation experiments using 50 male and 39 female images show the effectiveness of the proposed features for gender classification.

1. Methods for extracting biological features

1.1 Determination of the curve along with the throat

First, edges of a profile image are detected by the Canny algorithm which generates fewer noises and thinner edges than common edge detection methods such as the Sobel and Laplacian operator. The Canny algorithm can be roughly divided into four steps. First, to reduce the effect of noise, the Gaussian filter is applied to a profile image. Second, the edge strength and gradient direction are calculated, and an edge image is obtained by the Sobel operator. At the same time, the gradient direction is divided into four directions which are zero degree, 45 degrees, 90 degrees, and 135 degrees. Third, the non-maximum suppression is executed to reduce the thickness of the edges. Finally, the Hysteresis thresholding is applied to the edge image. Figure 1 (a) shows an edge image obtained by the Canny algorithm.

(a) (b)

Figure 1. An Example of Edge Image Obtained by the Canny Algorithm

Next, the authors describe how to extract the curve of the throat. It is ideal to extract the curve automatically by an edge detection method. However, existing methods for edge detection sometimes fail to detect the curve. Since this paper focuses on the efficiency of the proposed two features, we manually extract the neck region that includes the curve along with the throat. After that, to make the curve more clearer, the image is stretched into 1000 × 1000 pixels. And then, the nearest neighbor algorithm, as a pixel interpolation method, is applied to the image. Figure 1(b) shows the curve along with the throat obtained from the image shown in Figure 1 (a).

1.2 Feature extraction

First, average errors between the curve of the throat and a quadratic approximation curve are calculated. The line of the human's neck physiologically forms a gradient curve from the chin toward the neck. Therefore, it can be approximated by a quadratic curve. Compared with females, Adam's apples for males would be clearer. Thus, it is expected that the gap between the curve and its quadratic curve in a male profile image would be bigger than that in a female profile image.

Second, all the pixels in an edge image are scanned from the top to the bottom. Here, we define the horizontal direction of the images as x-coordinate and the vertical direction of the image as y-coordinate. Additionally, we define (x, y) = (0, 0) which is in the top left and (x, y) = (M, N) which is in the bottom right of the image. After defining all the coordinates, the scanning is conducted from the coordinate (0, 0) toward the horizontal direction until finding a pixel whose pixel value is not zero. Third, the proposed system records the coordinate of the pixel. Next, the scanning is conducted to the right-hand neighbor line from the recorded pixel, and continues scanning toward the vertical direction to find another pixel whose pixel value is not zero. The scanning above is executed until the coordinate of (M, N).

Next, the most plausible quadratic approximation curve is obtained from the recorded coordinates. In this paper, we use the least squares method to calculate the approximate curve. Here, the formula of the quadratic function can be defined as below

$$f(x) = a_2x^2 + a_1x + a_0 \tag{1}$$

where the errors between the secondary function and the actually measured data (x, y) can be obtained by the square difference between f(x) and y as below.

$$(f(x) - y)^2 \tag{2}$$

Regarding the total number of pixels for the recorded coordinates as n, the sum of the errors between n–th pixel and the approximate curve J is defined as below.

$$J = \sum_{i=0}^{n}(f(x) - y)^2 \tag{3}$$

Here, according to (1) and (3), J is defined as below.

$$J = \sum_{i=0}^{n}(a_2x_i^2 + a_1x_i + a_0 - y)^2 \tag{4}$$

Then, we evaluate the factors of a0, a1 and a2 to minimize the value of the error function. If we substitute the measured value of x and y, the error function J can be regarded as a secondary function about a0, a1, and a2. Since this secondary function is convex downward, we can obtain the minimum value of a0, a1, and a2. Here, we calculate the partial differentiation for each a as below.

$$\frac{\partial J}{\partial a_0} = 2\sum_{i=0}^{n}(a_2x_i^2 + a_1x_i + a_0 - y) = 0 \tag{5}$$

$$\frac{\partial J}{\partial a_0} = 2\sum_{i=0}^{n}(a_2x_i^2 + a_1x_i + a_0 - y) = 0 \tag{6}$$

$$\frac{\partial J}{\partial a_2} = 2\sum_{i=0}^{n}x_i^2(a_2x_i^2 + a_1x_i + a_0 - y) = 0 \tag{7}$$

And, we reorganize each equation of (5)× (7) as below.

$$na_0 + (\sum_{i=0}^{n}x_i)a_1 + (\sum_{i=0}^{n}x_i^2)a_2 = \sum_{i=0}^{n}y_i \tag{8}$$

$$(\sum_{i=0}^{n}x_i)a_0 + (\sum_{i=0}^{n}x_i^2)a_1 + (\sum_{i=0}^{n}x_i^3)a_2 = \sum_{i=0}^{n}x_iy_i \tag{9}$$

$$(\sum_{i=0}^{n}x_i^2)a_0 + (\sum_{i=0}^{n}x_i^3)a_1 + (\sum_{i=0}^{n}x_i^4)a_2 = \sum_{i=0}^{n}x_i^2y_i \tag{10}$$

The equation above can be represented by the matrix representation as below.

$$\begin{vmatrix} n & \sum_{i=0}^{n}x_i & \sum_{i=0}^{n}x_i^2 \\ \sum_{i=0}^{n}x_i & \sum_{i=0}^{n}x_i^2 & \sum_{i=0}^{n}x_i^3 \\ \sum_{i=0}^{n}x_i^2 & \sum_{i=0}^{n}x_i^3 & \sum_{i=0}^{n}x_i^4 \end{vmatrix} \begin{vmatrix} a_0 \\ a_1 \\ a_2 \end{vmatrix} = \begin{vmatrix} \sum_{i=0}^{n}y_i \\ \sum_{i=0}^{n}x_iy_i \\ \sum_{i=0}^{n}x_i^2y_i \end{vmatrix} \tag{11}$$

We use the Gaussian elimination method to solve Eq.11 and obtained value of a0, a1, and a2. The average errors D between the quadratic approximation curve and the recorded coordinates are defined as below.

$$D = \frac{1}{n}\sum_{i=0}^{n}\sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{12}$$

Finally, the parameter D is used as one of the features for gender classification. In addition, we propose to extract the width of the neck as another feature for gender classification. The width is calculated as the total pixels of the horizontal line between the central pixels of the curve along with the throat to the other side of the neck.

2. Experimental result

The authors have prepared 90 profile images obtained from a hair catalog on the Web site available at http://mico.allabout.co.jp/c_hairstyle/.The image data consists of 50 male profile images and 39 female profile images. From the web site, the authors selected profile images that have a single colored background, and are 500 pixels in height and 375 pixels in width.

There exist some widely-used benchmark datasets that

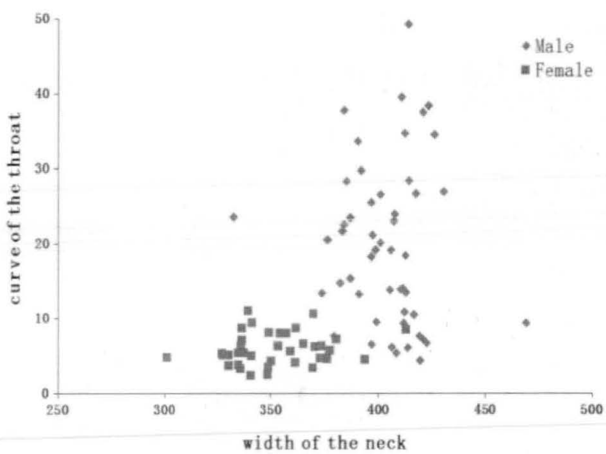

Figure 2. Distribution of the Two Features Extracted from the 90 Profile Images

include profile images such as CMU Image Data Base and UMIST Face Database. However, they cannot be used to evaluate the proposed method due to the following reasons. (a) The ratio between male and female images is imbalanced. This leads to the problem that the classification model tends to be biased to classify the majority samples. (b) Profile images are captured from different angles or different places. We assume that the proposed method is used in a situation that a concealed camera is placed at the side wall of a pathway.

As a classification algorithm, the authors have implemented the logistic regression from a widely used data-mining tool called Weka [6]. The parameters for the logistic regression were optimized in pre-experiments using the leave-one out cross validation.Specifically, one image was chosen as test data and the other images were used for training, and this procedure was repeated until all images were chosen as test data. After optimizing the parameters, the leave-one out cross validation was performed on the images.

Figure 2 shows the proposed two features extracted from the 90 profile images. In the figure, the vertical axis represents the value of the feature extracted from the curve along with the throat and the horizontal axis represents the value of the features measured with respect to the width of the neck. From the figure, we can see that the value of the curve in female images is less than 20 while that of 24 male images is larger than 20.

Table 1 shows classification results of the proposed method with the feature of the curve. Since the bump of the laryngeal prominence is unclear in approximately 30% of the 50 male images and invisible in 6 of 50 male images, we can say that this feature works well on gender classification.

Table 2 shows classification results with the feature of "width of the neck". And, Table 3 shows classification results with both of the features. Besides, as a comparable method for gender classification, we have implemented a LBP(Local Binary Patterns)-based method called SLBM [7]. Table 4 shows classification results obtained by SLBM. While SLBM shows over 90% accuracy for frontal images in previous study, it showed 86.5% accuracy for profile images. This suggests that it is more difficult to classify the gender for profile images than frontal ones.

From all the tables, we can see that the combination of the proposed two features have shown the highest performance in gender classification.

3. Discussion

From Figure 2, we can see that some of the male images have lower value than female ones with respect to the curve along with the throat. By observing the images, we found that the bump is not clear in the male images. This means that the feature does not work well for such images. However, since the bump for female images is usually invisible, the feature can be used to detect male images where the bump is clear. For example, when we configure the value 20 as a threshold for the feature,

	Male	Female	Average
Number of correctly classified images / Total images	41 / 50	36 / 39	77 / 86
Accuracy	82.0%	92.3%	86.5%

Table 1. Result in the Classification with the Feature Extracted from the Curve Along with the Throat.

	Male	Female	Average
Number of correctly classified images / Total images	47 / 50	36 / 39	83 / 89
Accuracy	94.0%	92.3%	93.3%

Table 2. Result in the Classification with the Feature of "Width of the Neck".

	Male	Female	Average
Number of correctly classified images / Total images	48 / 50	38 / 39	86 / 89
Accuracy	96.0%	97.4%	96.6%

Table 3. Result in the Classification with Both of the Features.

	Male	Female	Average
Number of correctly classified images / Total images	44 / 50	33 / 39	77 / 89
Accuracy	88.0%	84.6%	86.5%

Table 4. Result in the Classification with the Features Extracted by SLBM.

approximately 50% of male images would be correctly classified while no male ones are incorrectly classified.

From Figure 2, we can see that the feature of the width of the neck is effective on the gender classification. Besides, compared with the other features, the boundary between female images and male ones is clearer. However, the value of the feature becomes higher in female images when the hair is regarded as the neck region. In order to solve this problem, we need to distinguish the neck region from the hair region by using color information.

Conclusion

This paper has presented a gender classification using two biological features extracted from profile images. Evaluation experiments for 89 profile images have shown that both of the features work well on gender classification. Besides, when using the feature of the curve along with the throat, we confirmed that approximately, half of the male images could be correctly classified while no female ones were incorrectly classified.

As a future work, we would like to develop a method to determine the curve along with the throat and width of the neck automatically. Besides, we would like to analyze the dependence on the race and age for the proposed two features.

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