Facial Gender Classification Using LUT-Based Sub-images and DIE

Jong-Bae Jeon, Sang-Hyeon Jin, Dong-Ju Kim, and Kwang-Seok Hong

School of Information and Communication Engineering, Sungkyunkwan University, 300, Chunchun-dong, Jangan-gu, Suwon, Kyungki-do, 440-746, Korea
getset1@skku.edu, jinjinsh@skku.edu, radioguy@skku.edu, kshong@skku.ac.kr

Abstract. This paper presents a gender classification method using LUT-based sub-images and DIE (Difference Image Entropy). The proposed method consists of three major steps; extraction of facial sub-images, construction of a LUT (Look-Up table), and calculation of DIE. Firstly, extraction of sub-images of the face, right eye, and mouth from face images is conducted using Haar-like features and AdaBoost proposed by Viola and Jones. Secondly, sub-images are converted using LUT. LUT-based sub-regions are constructed by calculation of one pixel and near pixels. Finally, sub-images are classified male or female using DIE. The DIE value is computed with histogram levels of a grayscale difference image which has peak positions from -255 to +255, to prevent information sweeping. The performance evaluation is conducted using five standard databases, i.e., PAL, BioID, FERET, PIC, and Caltech facial databases. The experimental results show good performance in comparison with earlier methods.

Keywords: Gender Classification, Difference Image Entropy.

1 Introduction

Biometrics such as facial structure, fingerprints, iris structure, and voice can be used in many applications in fields such as human computer interaction, multimedia, security systems, and gate entrances. As time goes by, the research of facial image processing has become the focal point of many researchers' attention. Facial images have a lot of information including information about gender, age, expression, and ethnic origin. In this paper a method for gender classification is proposed. Not surprisingly, a lot of research on facial gender classification has been done by researchers from in the field of computer science. Our gender classification method consists of three major steps; extraction of facial sub-images, construction of LUT, and calculation of DIE. We propose a new gender classification system using Shannon's entropy-based DIE and LUT-based sub-images. The difference images are computed with pixel subtraction between input images and average images from reference images. For performance evaluation of the proposed method, we use five standard facial databases, i.e., PAL [1], BioID [2], FERET [3], PIC [4], and Caltech [5]. In addition, the proposed method is compared to the methods of using Euclidean with PCA and sobel image among the edge detection methods.

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This paper is organized as follows. In section 2, we review some related work on the research of gender classification. Section 3 describes the extraction method of sub-images of the face, eye, and mouth, basic concepts of the Difference Image Entropy (DIE), LUT-based sub-images and the method of the proposed facial gender classification. The experimental results are described in Section 4. Finally, we draw conclusions in Section 5.

2 Related Work

Earlier work on gender classification mainly originated in psychology and cognition research. Recently people began to consider this problem more technically. Several methods have been proposed for solving the gender classification problem. Among them, systems based on neural networks, PCA, decision trees, SVM, and AdaBoost classifiers can be mentioned [6]. Shakhnarovich et al. [7] proposed an AdaBoost-based gender classification method that achieved even better performance than SVM. In [8], a gender classification system is proposed based on the use of the SVM classifier. Other work includes Wu et al.'s LUT-based AdaBoost method that implemented a real-time gender classification system with comparative performance [9].

In 1948, Shannon introduced a general uncertainty-measure on random variables that takes different probabilities among states into account [10]. Given events occurring with probability *P*, the Shannon entropy is defined as Eq. (1).

$$H = \sum_{i=1}^{m} p_i \log \frac{1}{p_i} = -\sum_{i=1}^{m} p_i \log p_i \tag{1}$$

Shannon's entropy can also be computed for an image, where the probabilities of the gray level distributions are considered in the Shannon Entropy formula. A probability distribution of gray values can be estimated by counting the number of times each gray value occurs in the image and dividing those numbers by the total number of occurrences. In this method, Shannon entropy is also a measure of dispersion of a probability distribution [11], however this system is an entropy-based method for face localization. Recently, we proposed DIE-based teeth verification [12] and DIE-based teeth recognition [13].

3 A Proposal for Facial Gender Classification

The architecture for a DIE-based facial gender classification system using facial images consists of three steps. First, sub-images are extracted using Haar-like features and the AdaBoost algorithm. Second, extracted sub-images are made into LUT-based sub-images. Third, DIE is computed with the accepted input sub-image and average sub-image from male and female. Finally, the minimum value is selected via comparison processing of the DIE value and the facial gender result is returned to the user. The system flow-chart of a DIE-based biometric verification system using an LUT-based image is shown in Fig. 1.

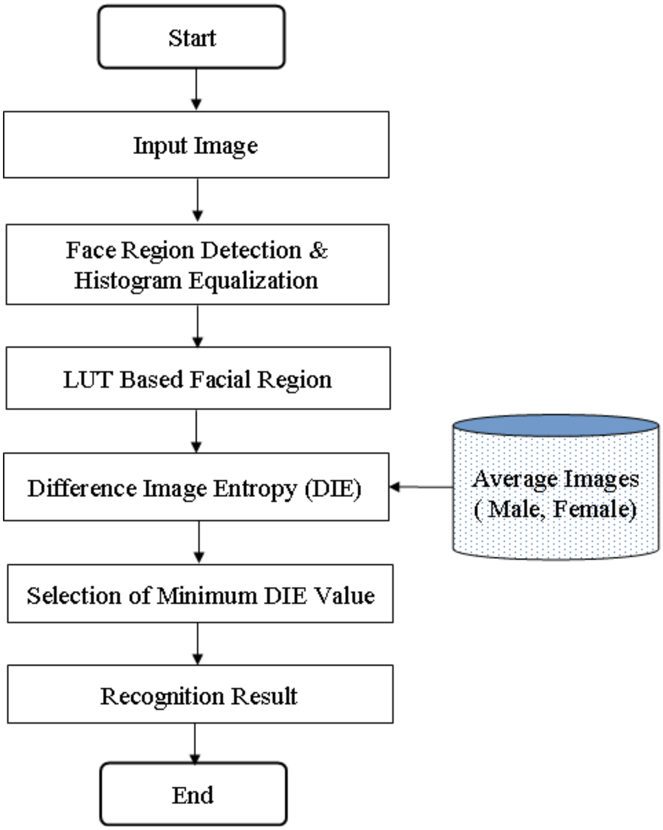

Fig. 1. Block Diagram of gender classification

3.1 Extraction of Sub-images from Original Image

In this paper, we extract three sub-regions from facial images as illustrated in Figure 2. The detection process for face, right eye and mouth regions use Haar-like features and the AdaBoost method introduced by Viola and Jones. Extracted sub-images are resized. The face is resized to 80x80 pixels, the right eye to 40x40 pixels, and the mouth to 50x30 pixels.

3.2 LUT-Based Sub-images

LUT is a data structure, usually an array or associative array, used to replace a run-time computation with a simpler array indexing operation. The LUT used in the proposed method is defined as the following Eq. (2) – (5). LUT is computed using pixel subtraction between a grayscale value of one pixel and the average value for three pixels around one pixel.

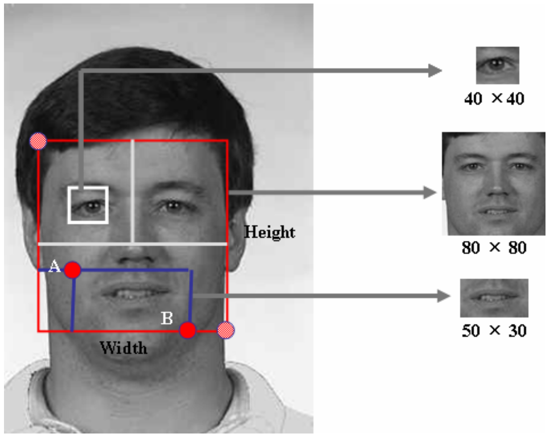

Fig. 2. Extraction of three sub-images from original image

$$\sum_{x=0}^{w-2}\sum_{y=0}^{h-2} LUT[y][x] = OI[y][x] - \{OI[y][x+1] + OI[y+1][x] + OI[y+1][x+1])/3\} \tag{2}$$

$$\sum_{y=0}^{h-2} LUT[y][w-1] = OI[y][w-1] - \{OI[y][w-2] + OI[y+1][w-2] + OI[y+1][w-1])/3\} \tag{3}$$

$$\sum_{x=0}^{w-2} LUT[h-1][x] = OI[h-1][x] - \{OI[h-2][x] + OI[h-2][x+1] + OI[h-1][x+1])/3\} \tag{4}$$

$$LUT[h-1][w-1] = OI[h-1][w-1] - \{OI[h-2][w-2] + OI[h-2][w-1] + OI[h-1][w-2])/3\} \tag{5}$$

In above equation, OI is the original sub-image, *y, x* indicates height and width indexes, and *w, h* indicates the width and height of sub-images respectively.

Finally, the pixel of LUT-based sub-images is added to a 100-gray value as shown in Eq. (6). The 100-gray value is an experimental value which is most suitable for gender classification.

$$\sum_{x=0}^{w-1}\sum_{y=0}^{h-1} \mathrm{Im}\, g[y][x] = LUT[y][x] + 100 \tag{6}$$

3.3 Difference Image Entropy

Difference Image Entropy is computed with histogram levels of a grayscale difference image which has a peak position from -255 to +255, to prevent information sweeping. The average image from the *M* reference sub-images is given in Eq. (7).

$$S_{average} = \frac{1}{M}\sum_{m=1}^{M} S_m(x,y) \tag{7}$$

In Eq. (7), $S_m(x,y)$ means the m^{th} reference image. The difference image (D_{diff}) is defined as Eq. (8). where D_{diff} is computed by pixel subtraction between input sub-images, I_{input} and average sub-images, and $S_{average}$ on random-collected gender reference images.

$$D_{diff} = I_{input} - S_{average} \tag{8}$$

The DIE, E_g is defined as Eq. (9), and P_k means probabilities of the frequency of histogram in difference images.

$$E_g = -\sum_{k=-255}^{255} P_k \log_2 P_k = \sum_{k=-255}^{255} P_k \log_2 \frac{1}{P_k} \tag{9}$$

In addition, a probability P_k is defined as Eq. (10). Where a_k indicates the frequency of histogram from the -255 histogram levels to +255 histogram levels, and the sum and total of each histogram in the difference images $G_{(T)}$ is given in Eq. (11).

$$P_k = \frac{a_k}{G_{(T)}} \tag{10}$$

$$G_{(T)} = \sum_{k=-255}^{255} a_k \tag{11}$$

4 Experiments and Results

4.1 Facial Databases

Experiments for gender classification involved five standard databases of facial images, i.e., FERET, PIC, BioID, Caltech, and PAL. The sample images of frontal faces are shown in Fig. 3. We used a total of 3,655 frontal face images, 2,078 males and 1,577 females. We used 660 images from PIC with 438 males and 222 females. We used 705 images from FERET, with 400 males and 305 females. We used 1,270 images from BioID, with 746 males and 524 females. We used 440 images from Caltech, with 266 males and 174 females. And, we used 580 images from PAL, with

Fig. 3. Samples from facial databases: (a) PAL, (b) FERET, (c) PIC, (d) BioID, (e) Caltech

228 males and 352 females. To make the average image for males and females, we used 1,040 and 790 images of men and women, respectively. Also, we use 1,038 images of males and 787 images females to evaluate the performance of the gender classification system.

Extraction of face, right eye, and mouth regions from facial images is performed by using Haar-like features and the AdaBoost algorithm. Facial regions are detected using the frontal face cascade. This face detector is scaled to the size of 24×24 pixels. The right eyes are extracted by our own training. The training process is implemented in a Microsoft Visual C++ 6.0 environment, simulated on a Pentium 2.6GHz machine. This right eye detector is scaled to the size of 24×12 pixels. We used 5,254 images for positive images of the right eye region and 10,932 images for negative images of the background. The training set consisted of five face databases and our own facial images acquired by webcam as shown figure 4.

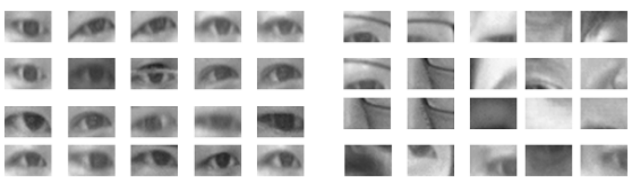

Fig. 4. Left: Right eye images (positive). Right: Non-right eye images (negative).

In order to perform gender classification experiments, the program needs to preprocess original facial images. The preprocessing step is described below. For grayscale images, extracted sub-images are converted into grayscale images and normalized using histogram equalization to minimize the effect of illumination. Next, sobel edge images and LUT-based images are made and converted in the gray level. Figure 5 shows male and female grayscale sub-images and the sub-images for sobel edge detected images and LUT-based images.

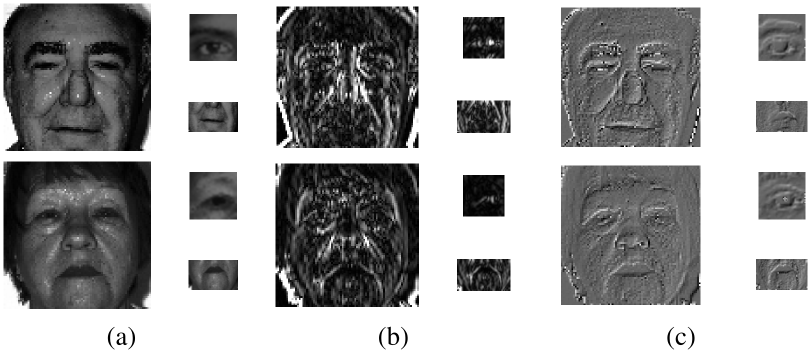

Fig. 5. The preprocessed sub-images: (a) grayscale images, (b) sobel edge detected images, (c) LUT-based images

Figure 6 shows the average image of sub-images for grayscale images, sobel edge detected images and LUT-based images. These average images are used to compute the DIE values with input images.

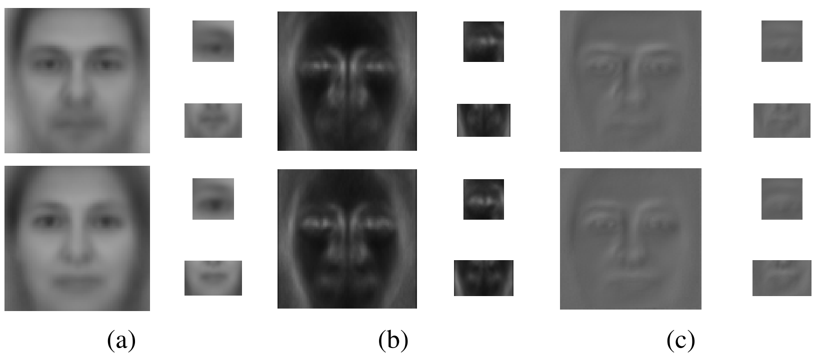

Fig. 6. The average images of sub-images:(a) grayscale images, (b) sobel edge detected images, (c) LUT-based images

4.2 Comparative Experiments

We tested four methods of facial gender classification. The first method was conducted using grayscale based sub-images and DIE for each sub-region. The second method was conducted using sobel edge images of detected sub-images and DIE. Thirdly, the proposed LUT-based sub-images and DIE method in the paper was tested for each sub-region. Lastly, the method of Principal Component Analysis (PCA) and Euclidean for each sub-region is conducted as comparative experiment.

The result of facial gender classification for sub-images is shown in Table 1 to Table 3. Table 1, Table 2, and Table 3 are results for the facial region, right eye region, and mouth region, respectively.

Table 1. Gender classification results for facial images

		Male	Female	Total
Grayscale image + DIE	Male	646/1038 (62.23%)	392/1038 (37.77%)	71.6%
	Female	126/787 (16.1%)	661/787 (83.9%)	
Sobel Edge Detected image + DIE	Male	203/1038 (19.5%)	835/1038 (80.5%)	52.7%
	Female	27/787 (3.5%)	760/787 (96.5%)	
LUT-based image +DIE	Male	815/1038 (78.5%)	223/1038 (21.5%)	74.3%
	Female	246/787 (31.3%)	541/787 (68.7%)	
PCA + Euclidean	Male	487/1038 (46.9%)	551/1038 (53.1%)	61.6 %
	Female	150/787 (19.1%)	637/787 (80.9%)	

Table 2. Gender classification results for right eye images

		Male	Female	Total
Grayscale image + DIE	Male	743/1011 (73.4%)	268/1011 (26.6%)	64.9%
	Female	354/765 (46.2%)	411/765 (53.8%)	
Sobel Edge Detected image + DIE	Male	870/1011 (86.5%)	141/1011 (13.5%)	55%
	Female	658/765 (86%)	107/765 (14%)	
LUT-based image +DIE	Male	691/1011 (68.3%)	320/1011 (31.7%)	61.2%
	Female	369/765 (48.2%)	396/765 (51.8%)	
PCA + Euclidean	Male	589/1011 (58%)	422/1011 (42%)	56.5%
	Female	350/765 (45.7%)	415/765 (54.3%)	

From the experiment results, it can be seen that the advantage of DIE is demonstrated. Also, LUT-based sub-images are better than grayscale sub-images and sobel edge detected sub-images. This method indicated classification rates with an overall classification rate of 74.3%. And the first, the second, and fourth methods showed a classification rate of 71.6%, 52.7%, and 61.6% for facial regions respectively. For the right eye region and mouth region, grayscale based images and the DIE method is 64.9% and 64.8% respectively. We can confirm two main results. First, the facial region indicated better performance than the right eye region and the mouth region. Secondly, the proposed LUT-based sub-images and the DIE method are generally better than three methods.

Table 3. Gender classification results for mouth images

		Male	Female	Total
Grayscale image + DIE	Male	606/1038 (58.3%)	432/1038 (41.7%)	64.8%
	Female	209/787 (26.5%)	578/787 (73.5%)	
Sobel Edge Detected image + DIE	Male	1030/1038 (99.2%)	8/1038 (0.8%)	56.9%
	Female	777/787 (98.7%)	10/787 (1.3%)	
LUT-based image +DIE	Male	241/1038 (23.2%)	797/1038 (76.8%)	38.7%
	Female	320/787 (40.6%)	467/787 (59.4%)	
PCA + Euclidean	Male	473/1038 (45.5%)	565/1038 (54.5%)	59.5%
	Female	174/787 (22%)	613/787 (78%)	

5 Conclusions

In this paper, the method to classify whether an input image is male or female was proposed by using DIE and LUT-based sub-images. We conducted gender experiments for sub-images and four gender classification methods. In classification results for comparative experiments, the proposed LUT-based sub-images and the DIE method showed better performance than remainder methods with a classification rate of 74.5% for facial region. From this result, we confirm that DIE-based methods give reliable gender classification results.

The gender classification system is expected to be applied to a live application in the field. In the future, it will be necessary to research more robust gender classification techniques including more variation in rotation, illumination, and other factors. Although we discuss the method of DIE on gender classification, it can be used in other facial expressions and age classifications. Also, more efforts should be paid on the combination of DIE and other pattern recognition algorithms.

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