Instruction for Authors on Paper Style

Age and Gender Recognition Using Facial Edge Information

Miyoko Nakano[1] **and Minoru Fukumi**[2]
[1] Yamanashi Prefectural University,
1-6-1 Ikeda, Kofu, Yamanashi, 400-0062, Japan
nakano@yamanashi-ken.ac.jp
[2] University of Tokushima, Dept. of Information Science and Intelligent Systems,
2-1, Minami-Josanjima, Tokushima, 770-8506, Japan
fukumi@is.tokushima-u.ac.jpt

ABSTRACT

In the marketing field, it is very useful to collect the customer data of age and gender etc. For age and gender recognition, this study focuses on the edge information that consists of all wrinkles in a face and also a neck. Density histogram in which the value of the edge intensity of the vertical direction and the horizontal direction in an image is greater than a threshold value is computed by using the edge feature extraction. They are treated as input data to a neural network (NN). These simulations are tried toward the face image database which collected face images of 15-64 years old. We perform the psychology experiment to know how humans are recognizing human's age. The result is compared with the result by NN. In order to show the effectiveness of the proposed method, computer simulations are carried out using these face images.

Keywords: age recognition, gender recognition, neural networks, facial edge information

1. INTRODUCTION

Human beings are easily able to distinguish person's age from an image of the face. In some cases, we can discern even identical twins. This ability has not been realized at computer vision. If it can be mounted in a computer, it may even identical twins. This ability has not been realized at be applicable to many fields. Research on age and gender estimation and recognition of facial expression from face images have increased recent years [1]-[5]. In particular, its application to age estimation is expected. For example, it can think that it is one of the technologies which are useful for the marketing investigation of examining a purchaser and a passer-by and so on [6]. Next information is important for age classification and gender classification from face images. One is shape information based on the frame of a face and the face muscle, and the other is texture information (such as soaks, the wrinkle and freckles) [1]. The first needs using the feature point extraction and carries out classification paying attention to the form of portions which constitute faces, such as an eye, a nose, and a mouth. However, it is difficult to extract these portions with high accuracy. There is a method which uses Gabor characteristics and a line shape distinction analysis as the research of paying attention to the automation without giving characteristics points [2], [3]. However, it is not easy that an age is estimated from a face image in such a case. Therefore, this research aims at age classification in large application area. In this paper, age and gender classification is tried for the HOIP face image database which collected face images of 15−64 year's old man and woman. Density histogram in which the value of the edge intensity of the vertical direction and the horizontal direction in an image is greater than threshold value is computed by using the edge information, and feature data is produced. For the meanwhile, neural networks (NNs) are advanced parallel systems, which are excellent especially in problems related to pattern recognition [6]. Accordingly, NN was used to classify a true and false smile[7]. Because, it was used to overcome the difficulty on class identification of nonlinear pattern recognition problems in a multidimensional space. By using NNs, the differences of feature data between ages are clarified and are discriminated in this paper. Finally, it is shown that the present approach is effective from simulation results

2. IMAGE DATA

In this paper, we perform some simulations using the above database of the face images.

1. 1. HOIP data base of the face images

HOIP database of the face images was built as a base of the research of face image in Human Object Interaction Processing (HOIP) in Japan. The characteristics of this data base are that photography directions are fixed. 300 Japanese images of 15-65 years old are divided into the interval of 5 years, each of which is composed of 15 persons. An image is the BMP file which consists of 635 × 480 pixels. Moreover, photography conditions are set as fixed; that means the same lighting condition, subjects, and camera position. The sample images of the front face are shown in Fig. 1.

Fig.1. The samples of HOIP's image data.

1. 2. Normalization of an image data

In order to perform computer simulations, it is needed to normalize original face images. The procedure of normalization is described below. At first, the center of a face image is adjusted at the intersection of two lines; the horizontal line which passes along under the both eyes, and the vertical line which passes through the middle of the eyebrows, and they are crossed as shown in Fig. 2. The center of position of an image is extracted. Then the line joining both eyes is moved so that it may become parallel to the horizon. Next, in order to reduce information other than a face, an image is cut out as shown in Fig. 1. Then, it is changed into the size of 100 × 100 pixels.

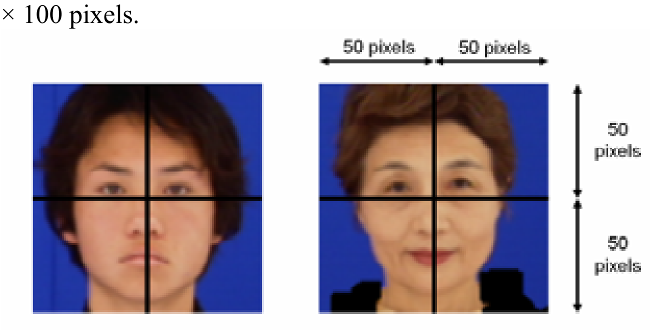


Fig.2. Normalization of the face image.

2. PROPOSED METHOD

The proposed method in this research is as follows:

1. A target image is normalized in the upper 100 × 100 pixels area from the neck as shown in Fig. 3.
2. The acquired face image is converted into a gray scale image.
3. The median filter is applied to the gray scale image, and a noise removal is done.
4. An edge is detected by the sobel filter.
5. A skin color area is extracted from the original image by the method using threshold values.
6. To yield feature data fed into the input units of NN, the pixels with the value edge intensity greater than 100 in the vertical direction and the horizontal direction are summed. The number of these pixels is the feature fed into NN.

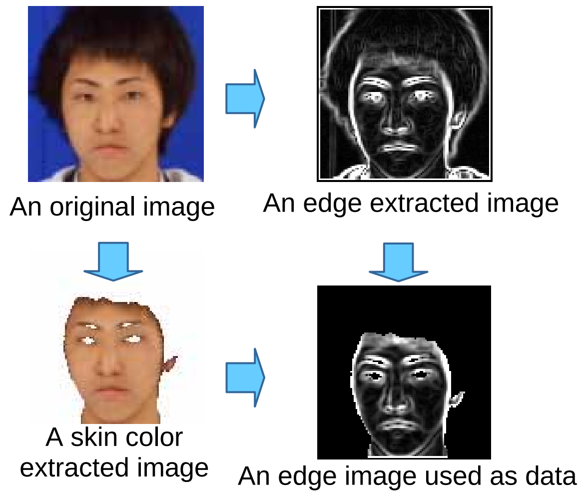


Fig.3. Procedures of an edge image.

3. COMPUTER SIMULATIONS

In order to show the effectiveness of the proposed method, it was applied to age and gender classification using real images.

3. 1. Skin color extruction

.

A skin color region (20 × 20 pixels) is extracted from 20 subject's face region in a database. Hue of the skin region is calculated from the following equation.

$$H = \left\{ \begin{array}{ll} \theta_1 & ; g \geq b \\ 2\pi - \theta_1 & ; g < b \end{array} \right\} \tag{1}$$

$$
\begin{aligned}
I &= R+G+B \\
r &= R/I,\ \ g=G/I,\ \ b=B/I \\
\theta_1 &= \cos^{-1}\frac{2r-g-b}{\sqrt{6\{((r-1/3)^2+(g-1/3)^2+(b-1/3)^2\}}}; \\
& 0 \le \theta_1 \le \pi
\end{aligned}
$$

The skin color region is extracted from an original image by using the maximum value and the minimum value of Hue.

3. 2. Structure of NN

In this study, a NN is used for the age and gender classification as the pattern recognition of similar faces. It is a three-layered NN. The BP method is adopted for learning [6]. All 200 data, the number of pixels, are used as input features fed into the input layer. The number of units of a hidden layer was decided experientially. The output layer has six units to classify six generations in age classification. In the case of Gender classification, it means discernment of man and woman. Therefore, the number of output units is one.

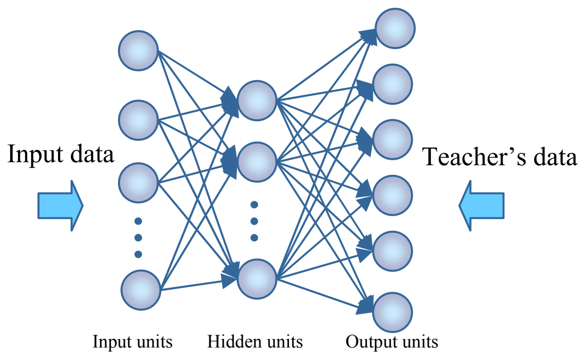


Fig.4. A NN model (three-layer class type)

Table1. Experimental conditions.

	age	gender
Input units	100+100	
Hidden units	20	15
Output units	6	1
Training rate	0.01	
Maximum learning times	30,000	

3. 3. Input data

This research is done by using the full color images of the BMP file. These subjects don't wear their glasses in an image to be used this time. Therefore, the number of the test data in Table 2, 3 is not the same in all classes. The total of the images is 252 sheets and another image of the same subject is not contained. In the case of age classification, a total of 120 sheets are used as the learning data and therefore 10 sheets for each age generation. The remaining data are used as the test data of computer simulations (Table2). For a gender classification, 140 subject's image is used as training data. The remaining subject's image is used for test data (Table3).

Table2. Input data for age classification.

Gender	Age	Learning data	Test data
M	10's	10	5
	20's	10	9
	30's	10	12
	40's	10	17
	50's	10	9
	60's	10	1
F	10's	10	5
	20's	10	18
	30's	10	17
	40's	10	19
	50's	10	18
	60's	10	2
Total		120	132
		252	

Table3. Input data for gender classification.

Gender	Age	Learning data	Test data
M	15 to 64	70	43
F	15 to 64	70	69

3. 4. Age classification

The result is shown in Table4. The threshold value is set to 200 in these experiments. The rate of an average accurate classification is 61.5%, which shows the classification of each age by using NN [6]. It is difficult to discriminate the man of adolescence or meridian of life. Therefore, in the case of 20's man, even if NN discriminated that his age is 10's or 30's, the discernment was judged to be correct in this paper. Thus, the rate of an average becomes 83.4%. In this table, reject's column denotes the rate of the data which did not respond to any unit in the output layer.

Table4. Result of age classification. (%)

	10's	20's	30's	40's	50's	60's	Reject
10's	90.0	10.0	0.0	0.0	0.0	0.0	0.0
20's	7.4	59.3	14.8	0.0	0.0	14.8	3.7
30's	3.4	17.2	41.1	13.8	6.9	3.4	13.9
40's	2.8	5.6	16.7	41.7	5.6	5.6	22.1
50's	7.4	0.0	11.1	14.8	37.0	29.6	0.0
60's	0.0	0.0	0.0	0.0	0.0	100	0.0

3. 5. Gender classification

The classification result is shown in Table5. When the result of man and woman was compared, the rate recognized to be a man was 93.0%, and the rate recognized to be a woman was 84.1%. The rate of an average accurate classification is 88.6%.

Table5. Result of gender classification.

Gender	Number of data	Successful number	Rate (%)
M	43	40	93.0
F	69	58	84.1

3. 6. Computer simulations using face area only

Computer simulation was done in the same way as a comparative experiment by using the image of only the face area. Example images are shown in Fig. 5. Other experimental conditions are the same as.

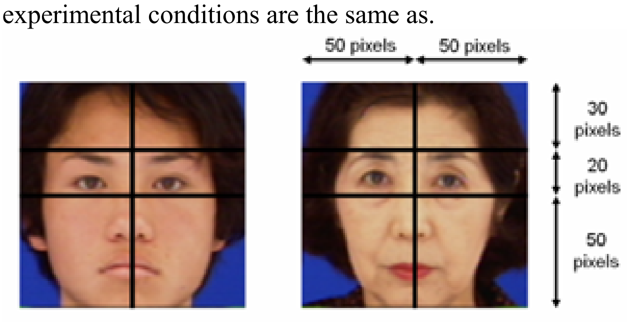


Fig.5. The sample image of comparative experiment.

The rate of an average accurate age classification is 74.5%, and gender classification is 86.2%. When we compared accuracy, the experiment using face and neck area was a better result than this experiment. The validity of the proposal method could be confirmed from this result as well. Therefore, it is thought that a neck area is important for age classification.

3. 7. Results comparison by changing the threshold

We gave arbitrary values for the threshold of a density histogram used as input data. In this section, we carried out simulations by changing the threshold. The results are shown in Table6, 7. The threshold value of 200 yielded the best result.

Table6. Age classification result changed the threshold. (%)

Threshold	Face and neck area	Face area only
100	68.4	58.6
150	74.7	70.3
200	83.4	74.5
240	82.9	64.0

Table7. Gender classification result changed the threshold. (%)

Threshold	Face and neck area	Face area only
100	84.2	76.2
150	81.0	80.0
200	88.5	77.2
240	87.5	81.0

4. COMPARATIVE EXPERIMENTS

In the proposal method, the value of edge intensity of the vertical direction and the horizontal direction was treated a feature data. In this section, a normalized face image (100 × 100pixels) is divided into small region (10 × 10pixels). In this experiment, the accumulation histogram of each small region is treated as feature data. The experimental condition is as follows.

Table8. Experimental condition.

Layer	The number of units	
	Age	Gender
Input	100	
Hidden	12	10
Output	6	1

The results are shown in Table 9, 10. It can be said that the accuracy of the experiment that uses the image that contains the neck region is good from this experiment.

Table9. Age classification result changed the threshold. (%)

Threshold	Face and neck area	Face area only
100	78.4	72.1
150	78.8	80.1
200	83.4	70.5
240	80.0	67.2

Table10. Gender classification result changed the threshold. (%)

Threshold	Face and neck area	Face area only
100	99.4	82.7
150	84.9	83.2
200	89.4	72.0
240	87.8	88.0

5. PSYCHOLOGY EXPERIMENT

Usually, we do not know a real age. We presume by a subjective evaluation such as watching at age and gender etc. It was done by using two kinds of data bases for 50 subjects. They are the color image-databases (A group) and the gray scale image-databases (B group).

The results are shown in Table11, 12. In the case of age classification, especially, subjects were recognizing it as shown in Table 13.

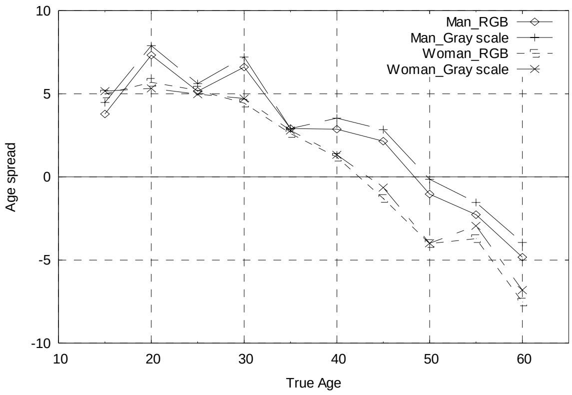
Table11. Accuracy of age recognition by the psychology experiment. (%)

Group	Age		Allowable limits(±10)	
	Man	Woman	Man	Woman
A	36.0	30.0	88.0	79.3
B	35.0	34.0	88.0	82.0

Table12. Accuracy of gender recognition by the psychology experiment. (%)

Group	Man	Woman
A	99.3	99.8
B	99.3	99.6

Fig.6. Difference of subject's recognition and true age.



4. CONCLUSION

As concerns gender recognition, the good result of about 90.0% was obtained. However, it was different from the result of the psychology experiment. In age recognition, although the permissible scope of classification was broadened, a high accuracy result was not obtained. The proposal method is effective when simplicity is taken into consideration.

REFERENCES

[1]. Young H. Kwon, Niels da Vitioria Lobo: Age Classification from Facial Images. Computer Vision and Image Understanding. Vol.74. 1 (1999) 1–21

[2]. B. Moghaddam and M. Yang: Gender classification with support vector machine. Proc. F&G2000. (2000) 306–311 3. M. Lyons, J. budynek, A. lane, and S. Akamatsu: Classifying facial attributes using a 2-d gabor wavelet representation and discriminant analysis. Proc. F&G2000. (2000) 202–207

[3]. Takayuki Fujiwara, Hiroyasu Koshimizu: Age and Gender Estimations by Modeling Statistical Relationship among Faces. KES2003. LNAI2774. (2003) 870–876

[4]. Noriko Nagata, Seiji Inokuchi: Subjective Age Obtained from Facial Images – How Old We Feel Compared to Others. KES2003. LNAI2774. (2003) 877–881

[5]. S. Akamastu: Computer Recognition of Human Face. IEICE Trans. on. Vol.D-II-J80. 8 (1997) 2031–2046 in Japanese

[6]. S.Y.Kung: Digital neural networks. PTR Prentice-Hall (1993)

[7]. M.Nakano, Y.Mitsukura, M.Fukumi, N.Akamatsu, and F.Yasukata: Natural Smile Recognition Using Simple PCA and Neural Networks. KES2003. LNAI2774. (2003) 631--637