Face Detection from Color Negative Film Using Flexible Template

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Abstract

We have proposed a new method for facial pattern detection from color negative film for exposure control in printing. The flexible template is introduced to measure the density distribution of facial region in color negative film. The template is divided into six sub-templates corresponding to eyes, cheeks, nose and mouth.The optimal boundaries in template are decided on the basis of the AIC theory (Akaike Information Criterion). The facial region is detected by using relationship between AIC value and density distribution in six regions and chromaticity value in each region. The detection experiment used 677 scenes taken by color negative film gave 80\% correct result.

Introduction

Large area transmission density (LATD) method has been widely used for exposure control in printing from color negative film. The method is based on the statistical practices that the average color of taking pictures is nearly neutral gray. The LATD method, however, is not always effective for the color correction of the image taken by incorrect light source, exposure and extraordinary scene such as red flower in the grass and yellow yacht on the sea. Therefore, many method have been proposed to decrease the color failure in printing. In color reproduction of printings, familiar colors such as skin, sky, grass are important, particularly the skin of facial patterns. In our previous papers, we introduced several methods to detect facial patterns from color negative films and television pictures used color of skin and lip and shape information of the pattern[3]. We also reported that the R,G,B density distribution in facial regions gives significant information for color correction in printing from color negative film.

In this paper, we introduced a new algorithm to detect facial pattern from color negative film by using the chromaticity of skin color and density distribution in facial regions measured by adaptive template and AIC value as shown in Fig. 1.

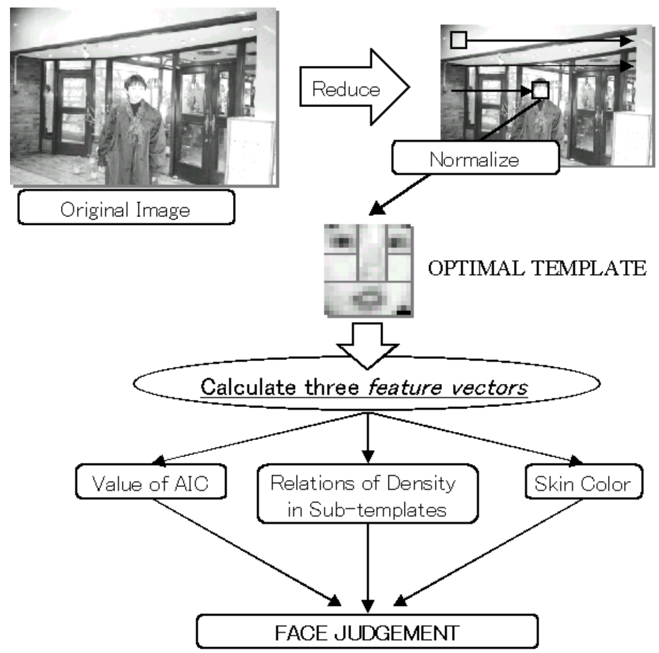

Figure 1.Schematic diagram to detect facial pattern

Adaptive Template to Measure the Density Distribution

Template matching technique has been used to detect facial region which is based on the density distribution characteristics in facial region. Those templates are calculated from a reference face and the correlation between the reference and test patterns, then the correlation coefficient is used to judge the facial pattern or not. Those classical template matching methods, however, are not significant for high accurate face detection because the distribution of density in facial region measured by template is dependent on the positions and directions of nose, eyes and mouth , and also taking conditions in dividual scenes.

In this paper, we present a new template matching method which can be adaptive to the various density distribution in facial region. The template is divided into six sub-templates corresponding to eyes, cheeks, nose and mouth as shown in Fig. 2. The boundaries in sub-template are flexible and the optimal boundaries are determined by the introduction of AIC theory. The value of AIC, relationship between each density measured by the sub-templates and skin color are used to judge the corresponding region is face or not. In this processing, though the size of template is fixed, the input image is reduced to different sizes from original image and the template is applied to those obtained images, therefore the template can be corresponded to detect various sizes of faces. The density distribution of input pattern was assumed as normal distribution with average 0 and variance 1, and optimal template was determined by AIC. Figure 1 shows the schematic diagram to detect facial pattern.

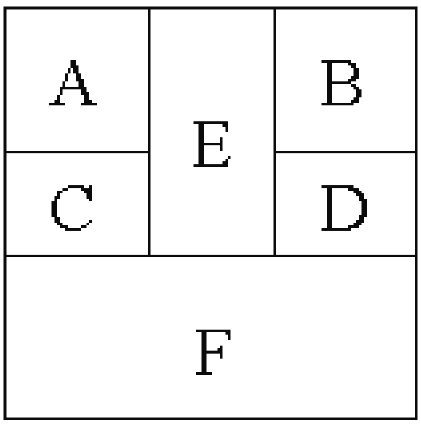

Figure 2. Flexible template

Determination of Optimal Template

The density histogram calculated by each sub-template except F is assumed as normal distributions. Histogram of region F may be represented as mixture of two normal distributions since the F includes both skin region F_1 and mouth region F_2. Here, we denote that the mean value obtained by sub-template F as m_F, then the pixel larger than m_F is classified into F_1 and pixel smaller than m_F is classified into F_2, because skin region is usually brighter than that of mouth. As mentioned above, boundaries in the template are flexible. In order to calculate optimal boundaries of template, we calculated AIC value of all possible combination of boundaries in the template. For certain arrangement of boundaries i, corresponding AIC to i is defined as follows.

$$\mathrm{AIC}_i = -2 \times \mathrm{MLL}_i + 2 \times \mathrm{k}_i, \tag{1}$$

where MLL_i denotes maximum log likelihood for arrangement i, and k_i is a total number of parameters of the model(in this case 2 × 7 for all i). AIC can be used to comparison of each model, and we consider that smaller value of AIC corresponds to be better model. Equation (1) is calculated as

$$AIC_i = 2\sum_r n_r \log \sigma_{ir} + K, \tag{2}$$

where n_r is a number of pixels in region r, and σ_{ir} is standard deviation of the region r, which r is correspondent to A; B; C; D; E; F1; F2. The value of AIC for all possible combination i is calculated and the arrangement corresponds to the smallest AIC was adapted as optimal boundaries. Examples of optimal template are shown in Fig. 3.

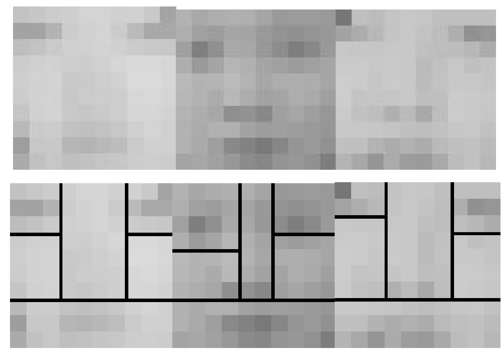

Figure 3. Examples of optimal template

Facial Pattern Detection Algorithm

As shown in Fig. 1, we used three feature vectors; (1) value of AIC, (2) relations of density distributions in each sub-template, (3) chromaticity in sub-regions to detect facial pattern. Each feature vector was determined as follows.

Value of AIC

It is considered that if the input pattern is face, the standard deviation in each sub-template will be low, thus the value of AIC to the optimal template becomes relatively low. On the other hand, if the input pattern is not face, it'll be considered two cases, namely the value of AIC to the optimal template will become to extremely large or small. Figures 4 and 5 shows the examples of template for non facial pattern which give extremely large and small AIC value, respectively. According to those mentioned conditions, the following AIC value is defined

$$\theta_{L1} < \textit{the value of AIC} < \theta_{U1}, \tag{3}$$

where θ_{L1} is lower threshold and θ_{U1} is upper threshold. Input pattern which dosen't satisfy Eq. (3) is classified as non-face. It is empirically known that the boundary between sub-template A and C is very significant for facial pattern detection. Therefore, we defined the condition as follow.

$$\theta_{L2} < AIC_{without} - AIC_{with} < \theta_{U2}, \tag{4}$$

where $AIC_{without}$ is the value of AIC without AC boundary and AIC_{with} is the value of AIC with AC boundary, θ_{L2} is lower threshold, θ_{U2} is upper threshold. On the other hand, AIC is proportional to a number of pixels belong to A and C regions, then the differences between the values of AIC calculated with and without AC boundary are divided as follow.

$$\theta_{L2} < \frac{AIC_{without} - AIC_{with}}{n_A + n_C} < \theta_{U2}, \qquad (5)$$

where n_A and n_C are the number of pixels belong to A and C regions, respectively. Similar conditions to Eq. (5) is also calculated by the boundaries BD, CF, DF. Furthermore, if the input pattern is face, then we can assume that the density of eye region has larger variance than the region of cheek. From this assumption,

$$\frac{\sigma_A}{\sigma_C} > \theta_{AC}, \qquad (6)$$

$$\frac{\sigma_B}{\sigma_D} > \theta_{BD}, \qquad (7)$$

where σ_i(i=A,B,C,D) is standard deviation of each reagion, θ_{AC}}, θ_{BD} are threshold between two regions A ~ C and B ~ D.

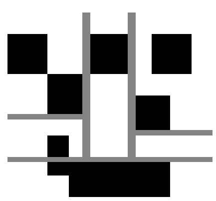

Figure 4. Example of optimal template correspond to high value of AIC

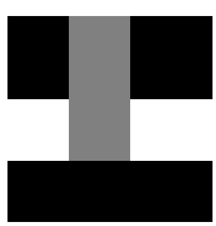

Figure 5. Example of optimal template correspond to low value of AIC

Relations of Density in Sub-templates

It is considered that eye and mouth regions have low reflectance compare to other regions. Let *I* be pixel value and *P*(*I*) be the normal distribution of pixel value in the region with the starting point of the arrow in Fig. 6 and I_{min} be the darkest pixel value in the region with the head of the arrow. Then the condition is represented as follows.

$$P(I_{min}) < \theta \ \textit{(for each arrow in Fig. 6)}, \qquad (8)$$

where θ is threshold.

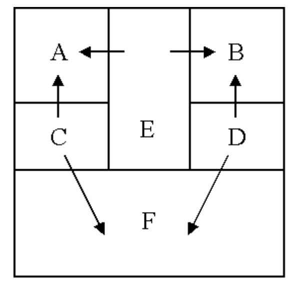

Figure 6. Relations among sub-templates

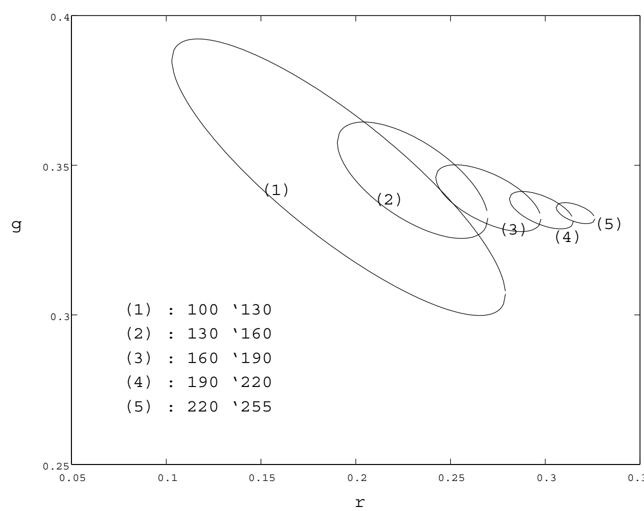

Figure 7. 95% confidence ellipsoids at each intensity interval

Skin Color

Many skin colors were measured from 677 color negative films with facial pattern, and the chromaticitis r, g of skin colors of those regions were calculated from 130 to 255 lightness units with interval ranges of 30 lightness units. Figure 7 shows regions of probability ellipse with 95% of those measured r, g chromaticities of skin color. If the r,g chromaticities of more than half of the pixels in sub-template C,D and E are inside of the ellipsoid distribution at confidence level at 95%, the input pattern was judged as facial pattern. The sub-template A,B,E are not used for judgment since they include eyes and mouth colors.

Experiment

Six hundred and seventy seven images recorded on the color negative film were processed and analyzed. Those images were taken under the various lighting conditions and each image contains one facial pattern. These color negative films were digitized with 8 bits quantization level and 256x384 pixels by a mechanical scanner. Each image is reduced by fixed rate of 0.2, 0.4, 0.6, 0.8 from original and without reduction. Three feature vectors were calculated by 677 pictures and facial patterns were detected from 540 pictures, namely 80% pictures were correctly discriminated. Examples of face detection are shown in Fig. 8. On the other hand, 10×10 template was used to detect facial pattern therefore we may define the discrimination ratio calculated by the total number of processing due to template. In this experiment, totally 30,686,577 input patterns were processed, pobabilty of false detection for each 10×10 input pattern was 725/30,686,577(0.003%). Examples of false detection are shown in Fig. 9.

Figure 8. Examples of face detection

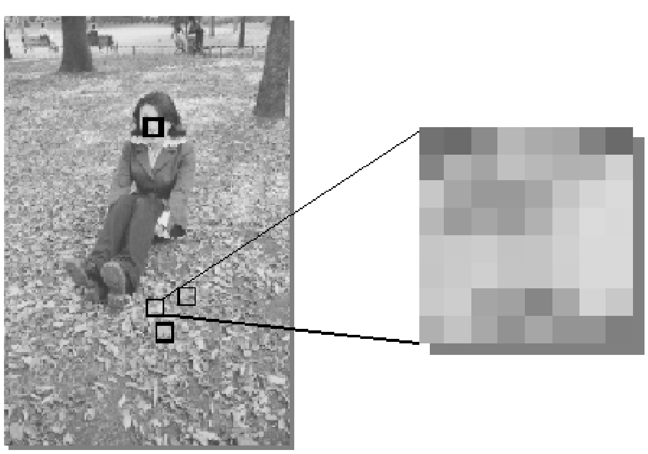

Figure 9. Example of false detection

Conclusion

We introduced a new method to detect facial pattern used flexible template, AIC and chromaticities. The experimental result showed that 80% of 677 images were correctly detected. We believe that the method is not only significant in exposure control of printing from color negative film but also in preferred color reproduction of digital hard copy.

Future Works

In the proposed method, most of false detections were presented by similar pattern to face such as cherry blossom and fallen leaves. It will be necessary to find feature vectors to discriminate those patterns as facial pattern.

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References

1. Hideo Natori, "Extraction of information for automatic density correction from color negative films.", Master thesis(Chiba University, 1997).
2. Damas Sanger, Hideaki Haneishi, and Yoichi Miyake, "Method for Light Source Discrimination and Facial Pattern Detection from Negative Color Film", Journal of Imaging Science and Technology, Vol.39, No.2, pp.166-175(1995).
3. Damas Sanger, Yoichi Miyake, Hideaki Haneishi, and Norimichi Tsumura, "Algorithm for Face Extraction Based on Lip Detection", Journal of Imaging Science and Technology, Vol.41, No.1, pp.71-79(1997).
4. Brian Scassellati, "Eye finding via face detection for a foveated,active vision system", Proceedings of the American Association of Artificial Intelligence Conference(AAAI-1998), AAAI Press.
5. Kah-Kay Sung ,Tomaso Poggio, "Example-Based Learning for View-Based Human Face Detection", IEEE Transaction on pattern analysis and machine intelligence, vol.20, No.1, pp.39-51(1998).