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A closed-loop algorithm to detect human face using color and reinforcement learning*

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Abstract: A closed-loop algorithm to detect human face using color information and reinforcement learning is presented in this paper. By using a skin-color selector, the regions with color "like" that of human skin are selected as candidates for human face. In the next stage, the candidates are matched with a face model and given an evaluation of the match degree by the matching module. And if the evaluation of the match result is too low, a reinforcement learning stage will start to search the best parameters of the skin-color selector. It has been tested using many photos of various ethnic groups under various lighting conditions, such as different light source, high light and shadow. And the experiment result proved that this algorithm is robust to the varying lighting conditions and personal conditions.

Key words: human face detection, skin-color selector, reinforcement learning
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INTRODUCTION

In recent years, there is an increasing interest in facial image understanding, and in these applications, human face detection plays a very important role. A good algorithm of face detection should have:

1. No restrictions on the personal conditions, such as ethnic group, age and sex.
2. No restrictions on the face image, such as the position, size direction and number of faces.
3. No restrictions on the background of the image
4. No restrictions on the lighting conditions, such as light source, illumination geometry and the chromatic characteristics of illumination.

The related work can be divided into two classes. The first class is based on a face-shape model. The face can be detected by template, (Yuille et al., 1996, Huang, et al., 1992, Yang et al., 1994, Miao Jun et al., 1999, Sung et al., 1998) or by neural network (Rowley et al., 1998), or by eigenface (Turk et al., 1996). It has less restriction on the lighting conditions. However, it still has some restrictions on the face direction and size. Some works used a pyramid of the input image to overcome the face scale problem, but they were still time-consuming due to the large data volume. These disadvantages limit the applications of these works in some cases that need fast and robust detection.

The second class uses color information, (Wu et al., 1996, Saber et al., 1998, Lee et al., 1996, Wu Haiyuan et al., 1999, Birchfield 1998), the basic idea of which can be depicted with a two-stage diagram. In the first stage, image regions with the color "like" human skin are selected as candidates of human face regions. The most commonly used skin-color selector is a fixed range in the color feature space. Then in the second stage, these candidates are matched with a face model. It is obvious that the performance of these works mainly depends on the skin-color selector. And experiments proved that there are two factors adversely affecting the performance of the skin-color selector: the first problem is the skin color difference

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between different ethnic groups and the second is the hue shift caused by different lighting conditions. Some of these works tried to overcome these two problems with the statistics of a large sample set. The implicit hypothesis is that the sample set has enough samples to reflect the distribution of skin color features of variant ethnic groups and variant lighting conditions. But it is very difficult to build such a sample set in the real life, and experiment proved that the performance was adversely affected while the processing photo was taken under different conditions with the sample set. So some more adaptive methods should be used to overcome these problems.

In order to obtain a fast processing speed, the basic idea of the second class was used in our algorithm but a closed-loop procedure was introduced to overcome the problems mentioned above. As shown in Fig.1, The range parameters of the skin-color-selector in our algorithm was not fixed but decided by a neural network with the input of color feature histogram. And when the candidates were matched with the face model in the second stage, they would get an evaluation representing the match success degree. Using the evaluation as the feedback, a reinforcement-learning module directed the neural network to search online the best parameters of the skin-color selector. Experiments showed that compared to other algorithms, the proposed algorithm was more robust to varying lighting conditions.

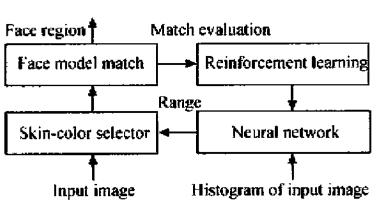


Fig.1 Block diagram of proposed method

ALGORITHM

1. Color features and skin color selector

The apparent color of an object under constant illumination can be simplified as shown in Eq.(1). I_r, I_g, I_b are the illumination in red, green and blue channels. And C_r, C_g, C_b are the reflection factors, which are decided by the color features of the object. Considering that the illumination in day life is almost a white light, the ratio of red to green and the ratio of yellow to blue can almost represent the color character of the object as shown in Eq.(2). The yellow segment can be estimated using red and green segments as shown in Eq.(3). Because the skin color clusters in a sector of the x-y plane, the polar coordinates were chosen to conveniently present the color features. For a pixel with color features of (θ, r), the output of the skin-color selector is shown in Eq.(4). The regions with the output 1 of the selector are candidates for face model matching. T_1, T_2, T_3, T_4 are four range thresholds of the skin-color selector. Image edges (Wang, et al. 2000) are then used to obtain more accurate segmentation results.

$$\begin{cases} Red = C_r I_r \\ Green = C_g I_g, \\ Blue = C_b I_b \end{cases} \quad (1)$$

$$\begin{cases} x = \dfrac{Red}{Green} \approx \dfrac{C_r}{C_g} \\ y = \dfrac{Yellow}{Blue} \approx \dfrac{C_y}{C_b} \end{cases}, \quad \begin{cases} \theta = \arctan(x, y) \\ r = \sqrt{x^2 + y^2} \end{cases}, \quad (2)$$

$$Yellow = \sqrt{Red \cdot Green}, \quad (3)$$

$$\mathrm{Selector}(\theta, r) = \begin{cases} 1 & \text{if } T_1 \leqslant \theta \leqslant T_2 \text{ and } T_3 \leqslant r \leqslant T_4 \\ 0 & \text{else} \end{cases} \quad (4)$$

(1 means skin color range)

2. Face model matching

In this module, some physiological features of human beings are used to test the candidates. There are two stages of coarse-to-fine hypothesize-and-test. In the first stage, an ellipse model is used to match every candidate region as a coarse template. This is based on the hypothesis that if the region is a human face, the region's shape should be close to an ellipse. And because the ratio of the major and minor axis of the ellipse should be in a constant range when it is a real human face region, the candidates that cannot satisfy this restriction would be deleted first. Supposing that the candidate region is R and the region within the respective ellipse is E, a score S_1 is given by Eq.(5) to evaluate the success degree of the matching with the ellipse. In the second stage, eyes and mouth will be searched in the candidate ellipses with the method suggested by Zhong Jingtu (2000). Although some researchers also used nose as a feature, it is proved by experiments that the nose is not as apparent as the eyes and mouths when there is highlight on the face. In order to decrease computation, only eyes and mouth were used as the facial features in our algorithm. And a score S_2 is given by Eq. (6) to evaluate the success matching degree in this stage. Eq.(7) gives the final score S of each candidate. The highest score would be delivered to the reinforcement-learning module as the evaluation of the match success until the highest score was over a threshold. And then the candidates with the highest score were considered as face regions.

$$S_1 = \frac{n(E \cap R)}{n(E \cup R)} \tag{5}$$

$n(R)$ is the number of points in the region R.

$$S_2 = \begin{cases} 0.5, & \text{no eyes or mouth found} \\ 1, & \text{find eyes or mouth, but not both} \\ 4, & \text{find both eyes and mouth} \end{cases} \tag{6}$$

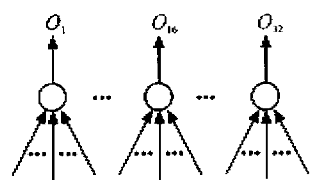
$$S = S_1 S_2 \tag{7}$$

3. Reinforcement learning

The reinforcement learning is an important machine-learning paradigm. As defined by Peng 1998, it is a framework for learning how to make a sequence of decisions in an environment. As an unsupervised learning method, it learns directly from the feedback of environment, which enable the system with reinforcement learning to learn online and be adaptive to the varying environment.

In our algorithm, a neural network using the histogram of the color features as its input was introduced to obtain the four thresholds of the skin-color selector. And this neural network was trained using the reinforcement-learning framework. Although the reinforcement learning can learn online, an offline learning stage was still used to obtain the default weights of the neural network. At the very beginning of processing a new image, these default weights were used to obtain color range parameters of the skin-color selector, and if the result was not satisfactory, the online learning would start to modify the weights of the neural network until the result was satisfactory.

As shown in Fig.2a, the neural network had 32 cells and each had one input vector x_1, x_2, $\cdots$, $x_n]^t$ representing the histograms of the two color features and one binary output representing one bit of the color range thresholds (every threshold had 8 bits). The output of the neural cells is determined by the function as shown in Eq.(4). The online training diagram was shown in Fig.2b. The offline training is a little different. After processing every image in the training set, the training is focused only on the photos with the lowest evaluation, which can avoid the extreme training and accelerate the training speed.



(a)

1. Get histograms of the color features of the input image;
2. Get the four parameters via Eq.4;
3. Get the candidates;
4. Match the candidates and get the evaluations;
5. If the evaluation is satisfactory then stop;
6. Modify the weights via Eqs.5;
7. Go to step 2

(b)

Fig.2 The reinforcement learning in proposed algorithm
(a) the architecture of the neural network;
(b) diagram of learning

$$O_i = \begin{cases} 0, & \text{if } y_i < p \\ 1 & \text{if } y_i \geq p \end{cases}, \quad y_i = f(\sum_j w_{ij} x_j) \tag{8}$$

p was a predefined threshold, w_{ij} was the weight of the neural network, and

$$f(x) = 1/(1 + e^{-x})$$
$$\Delta w_{ij}(t) = a(S(t) - \bar{S}(t-1))(O_i(t) - O_i(t-1))x_j(t) - b w_{ij}(t-1) \tag{9}$$

$$S(t) = \lambda S(t-1) + (1-\lambda)S(t)$$
$$O(t) = \gamma O(t-1) + (1-\gamma)O(t) \tag{10}$$

$S(t)$ is the score at time t.

EXPERIMENT RESULTS

We collected 500 photos taken under variant lighting conditions and including different people of variant personal conditions. Among them, 100 photos were used as the offline training samples.

1. Offline training of the skin-color selector

To accelerate the offline training, a simplified matching module was introduced. The real face regions in the training photos were extracted by hand as the respective correct results. If the result of the skin-color selector was R and the correct result was C, the evaluation v was defined by Eq. (11), which represented the similarity of R and C. The offline training had two stages. In the first stage, the neural network mentioned in Section2.3 processed every image in the training set and the inputs and outputs of the neural network and the evaluation were recorded. In the second stage, the image with the lowest evaluation value was selected to train the neural network using Eq. (11) as described in Section2.3. This loop was continued until the average evaluation of the training set reached a threshold, which was 0.9 in our experiment.

$$S(R,C) = \frac{n(R \cap C)}{n(R \cup C)} \qquad (11)$$

$n(R)$ is the number of the pixels in the region R.

2. Test of the algorithm

400 photos were chosen as test sample set in this experiment. Some were downloaded from the Internet while the others were taken in our lab. The images were taken under fluorescent lamp light, flashlight, tungsten light, sunlight and mixtures of these lights. Although most of them were of indoor scenes, 21 photos were of outdoor scenes. The face size varied from 20×28 pixels to 220×240 pixels. Among them, 120 photos were of Asian faces, 130 photos were of African faces and the others were of Caucasian faces. This algorithm was tested on a PC with Pentium II 233 CPU. And in this experiment, the worst consuming time was within 500ms to process an image with 512×256 pixels. And the average consuming time was about 300 ms.

As shown in Fig. 3, the highlighting and shadowing did not harm the performance of the proposed method, because the reinforcement learning method can find the best parameters of the skin-color-selector adaptively. The proposed method is also valid when there are multiple faces in the image as shown in Fig. 3, but these faces should not be occluded too much because the face model matching will fail if eyes and mouths can not be found in the region. Table 1 shows the test result. And the four failures were mainly caused by the worst lighting conditions. One failure was caused by the blue light that changed the face color into purple and the others were caused by the dim light which made the face color so dark that the color information was lost.

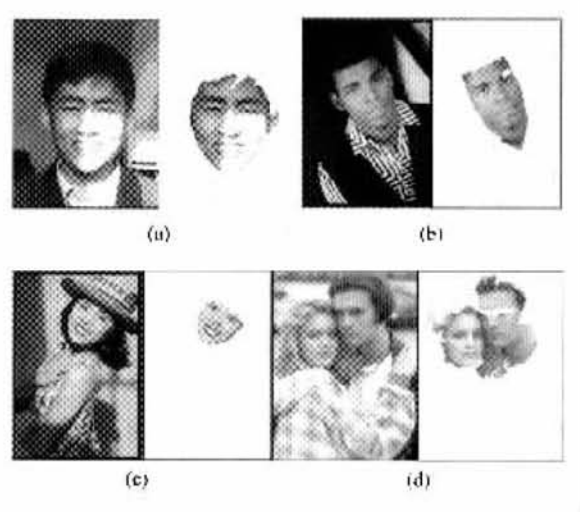


Fig.3 Experiment results

(a) a partially highlighted face and its result
(b) a face of an African and its result
(c) a face of a Japanese and its result
(d) two of Caucasian faces and the result

Table 1 Test results

Total test image number	Success image number
400	396

CONCLUSIONS

In this paper, we present a new face detection algorithm based on color information. And a reinforcement learning framework was introduced to improve the robustness of the algorithm. The experiments proved that this algorithm detected the face fast and robust enough.

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