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Real-Time Rotation-Invariant Face Detection Using Combined Depth Estimation and Ellipse Fitting

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***Abstract*:** This paper reports a combined depth- and model-based face detection and tracking approach. The proposed algorithm consists of four functional modules; i) color-based candidate region extraction, ii) generation of the depth histogram for handling occlusion, iii) rotation-invariant face region detection using ellipse fitting, and iv) face tracking based on motion prediction. This technique solved the occlusion problem under complicated environment by detecting the face candidate region based on the depth-based histogram and skin colors. The angle of rotation was estimated by the ellipse fitting method in the detected candidate regions. The face region was finally determined by inversely rotating the candidate regions by the estimated angle using Haar-like features that were robustly trained robustly by the frontal face.

***Keywords*:** Real-time face detection, Ellipse fitting, Depth histogram

1. Introduction

Face detection is of great importance in the computer vision and pattern recognition fields, and has many applications such as human-computer interaction, intelligent monitoring, face synthesis and object-based coding [1]. Viola et al. [2] proposed a feature-based face detection method using the Adaboost algorithm. Although Viola et al.'s method works well with frontal faces, it often fails to detect slanted faces. Linehart first proposed a method to detect specially rotated face regions, and extended it to multi-view face detection based on Viola et al.'s method [3]. Although color-based methods are robust to variations in rotation and scale, but they cannot deal with complicated background or occlusion [4]. Generally, a face detection method based on skin color is affected by the illumination conditions and camera characteristics [5, 6].

This paper presents a robust face detection algorithm to overcome both occlusion and variable orientation problems with the following four functional modules: i) A candidate of the face region is first detected using skin color, ii) a depth histogram is generated using a stereo camera, iii) the face region is finally determined by fitting the candidate region to an ellipse, and iv) the detected face region is tracked by appropriately predicting the motion of the region. Fig. 1 gives a flow-chart of proposed algorithm.

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2. Face Region Extraction Using Decorrelated Skin Color and Depth Information

The face candidate regions were detected using a decorrelated skin color component and depth information. The chromatic red component in the YCbCr color space, which was first utilized in reference [7], was used to decorrelate the skin color. The chromatic red (Cr) component can extract and compensate for an error signal. The skin regions are detected using the Cr and error components of ranges, R_{ES}=[0.02511,0.1177] and R_{Cr}=[135,173], which are the experimentally obtained error signal and Cr component, respectively [8]. The skin color segmentation process is defined as:

$$f_{skin}(x) = \begin{cases} 1, & \text{if } E(x) \in R_{ES} \text{ and } Cr(x) \in R_{Cr} \\ 0, & \text{otherwise} \end{cases} . \quad (1)$$

A color-based segmentation algorithm, however, is sensitive to occlusion in a complex background. The

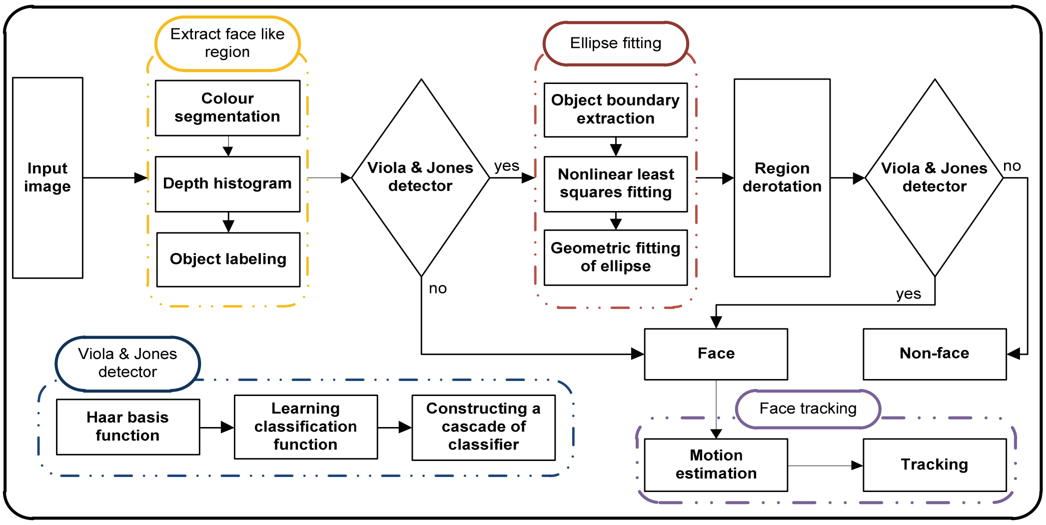


Fig. 1. Flow-chart of proposed algorithm.

following depth histogram of candidate regions was used to overcome this problem:

$$f_{depth}(x) = \begin{cases} 1, & \text{if } th_{front} < d(x) < th_{back} \\ 0, & \text{otherwise} \end{cases}, \tag{2}$$

where d represents the depth map of an image acquired by a stereo camera, and th_{front} and th_{back} are the threshold values of the foreground and background, respectively. The th_{front} and th_{back} values were 30 cm and 80 cm, respectively. Each region is divided according to the histogram. The best candidate region was selected as the final face region as follows:

$$f_{face}(x) = \begin{cases} 1, & \text{if } f_{skin}(x) = 1, \text{ and } f_{depth}(x) = 1 \\ 0, & \text{otherwise} \end{cases}. \tag{3}$$

3. Rotation-Invariant Face Detection and Tracking

Although Viola et al.'s face detection method is fast and accurate; it is sensitive to the training set. In particular, if faces have various poses, a non-face region can be detected erroneously. To overcome this problem, the angle of rotation was estimated and the region was rotated inversely using only front and side faces. The proposed algorithm first detects the front and side candidate regions, and the remaining candidate areas were fitted to the ellipses to estimate the orientation. After inversely rotating the slated face region, Viola et al.'s method was applied to determine the final face.

3.1 Rotation-Invariant Face Detection Method

In this study, the face region was detected using robust features trained by the front and side faces. An ellipse is determined uniquely by the centre of mass $(\bar{x}, \bar{y})$, orientation θ, length of the major axis α, and length of the minor axis β. The centre of mass was derived as follows:

$$(\bar{x}, \bar{y}) = \left(\frac{1}{A}\sum_{(x,y)\in C} x, \frac{1}{A}\sum_{(x,y)\in C} y\right), \tag{4}$$

where A represents the area of the face region. The orientation θ was derived using the centre of mass as follows:

$$\theta = \frac{1}{2}\arctan\left(\frac{2\mu_{1,1}}{\mu_{2,0} - \mu_{0,2}}\right), \tag{5}$$

where $\mu_{p,q}$ is defined as:

$$\mu_{p,q} = \sum_{(x,y)\in C} (x-\bar{x})^p (y-\bar{y})^q. \tag{6}$$

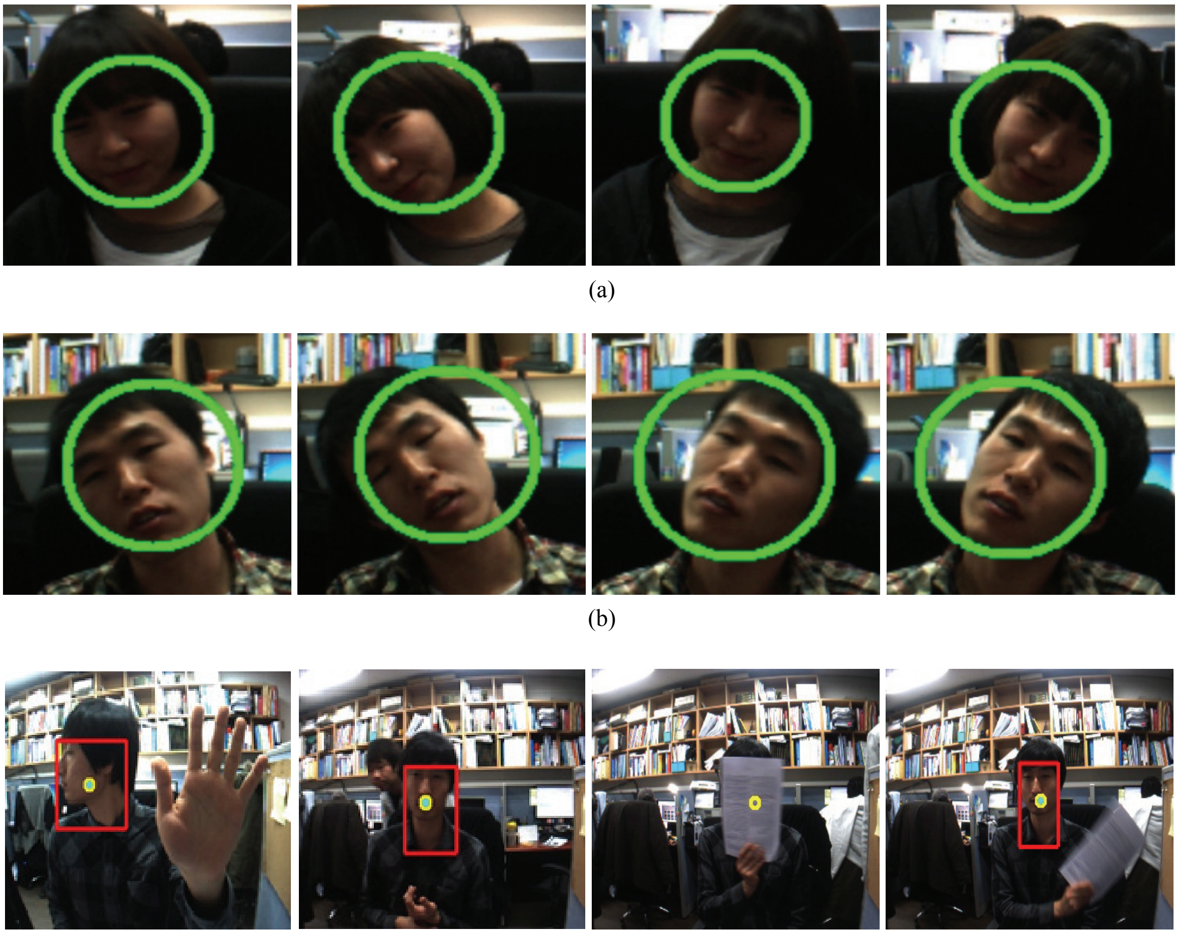
Finally, α and β were respectively calculated using

$$\alpha = \left(\frac{4}{\pi}\right)^{1/4}\left[\frac{I_{\min}^3}{I_{\max}}\right]^{1/8}, \text{ and } \beta = \left(\frac{4}{\pi}\right)^{1/4}\left[\frac{I_{\max}^3}{I_{\min}}\right]^{1/8}, \tag{7}$$

where $I_{\min}$ and $I_{\max}$ are defined as:

$$\begin{aligned} I_{\min} &= \sum_{(x,y)\in C} [(x-\bar{x})\cos\theta - (y-\bar{y})\sin\theta]^2, \text{ and} \\ I_{\max} &= \sum_{(x,y)\in C} [(x-\bar{x})\sin\theta - (y-\bar{y})\cos\theta]^2. \end{aligned} \tag{8}$$

Given the above parameters by ellipse fitting, the rotation matrix was generated using $(\bar{x}, \bar{y})$ with the rotation angle θ. The inversely rotated face was then



(a)

(b)

(c)

Fig. 2. Results of the proposed algorithm; (a) and (b) results of detecting difference faces and angles [15˚, 45˚], and (c) result of tracking an occluded face.

estimated by a geometric transformation using the rotation angle θ. The inversely rotated candidate region was used to detect the correctly rotated faces using Viola et al.'s method.

3.2 Face tracking with Occlusion Handling

This subsection presents a robust face tracking algorithm. Although the face region can be detected accurately in a single frame, the detection might fail in another frame if the face region is partially occluded by an object. If the occlusion occurs in a specific frame, the motion vector of the center of the face regions for robust tracking can be predicted. The face center is then calculated by averaging three points as follows:

$$\left(\frac{x_1+x_2+x_3}{3},\frac{y_1+y_2+y_3}{3}\right). \tag{9}$$

The difference between the current and previous frames is defined as the motion vector, F_{move}, which can be used as a prediction parameter in the event of an occlusion. In other words, if a face region disappears by occlusion, the face location can be predicted by adding F_{move} to the center of the previous frame. The proposed tracking algorithm is based on the linear motion model of the face.

4. Experimental Results

640x480 indoor video sequences were used to evaluate the performance of the proposed algorithm. The test images included both low light level conditions and a complicated background. To detect the face candidate regions, the skin regions were segmented using the skin tone color and depth-based histogram. Fig. 2 shows the results of the proposed algorithm.

For two different faces with four orientations in the range [15˚, 45˚], the proposed algorithm provides correctly detected face regions and the correct trajectories of the centre of the region as a result of the motion-based face tracking algorithm. The current location of the object trajectory provides a migration path for a motion estimation to predict the amount of overlapping in two objects.

The proposed face detection method was compared with Viola et al.'s and LAB color space-based methods.

The experiment used 31 images in the Caltech database. Viola et al.'s face detection method provided a success and error rate of approximately 93.55% and 19.35%, respectively, whereas the LAB color space-based method gave a significantly lower detection rate. The proposed method gave the same performance as Viola et al.'s method for upright faces.

Table 1. Comparison of the face detection rates for 31 upright face images using Viola et al.'s, LAB color space-based, and the proposed methods.

Face detection method	LAB-based face detection method (DETECTION/NUMBER OF IMAGES)	Viola's method [2] (DETECTION/NUMBER OF IMAGES)	PROPOSED ALGORITHM (DETECTION/NUMBER OF IMAGES)
Detected rate (success / number of image)	16/31	29/31	29/31
Error rate (fail / number of image)	19/31	6/31	4/31

Table 1 compares the face detection results of the proposed method with Viola et al.'s method for variously rotated faces. As shown in Table 2, the success rates of Viola et al.'s method became significantly low as the face was rotated by 15˚ or more, whereas the proposed method maintained high success rates regardless of the amount of rotation up to 45˚.

Table 2. Comparison of the success rates of rotated faces up to 45˚.

The rotated angles	Viola's method[2]	Proposed method
0˚	94%	94%
5˚	94%	94%
10˚	90%	94%
15˚	59%	94%
20˚	59%	90%
25˚	6%	94%
30˚	0%	94%
35˚	0%	94%
40˚	16%	90%
45˚	6%	94%

5. Conclusion

A novel face detection and tracking algorithm for solving both rotation and occlusion problems is proposed. The depth histogram of candidate regions generated by a stereo camera for solving the occlusion problem was used. Moreover, ellipse fitting was performed in the detected candidate regions to estimate the angle of rotation. Based on the extended set of experimental results, the proposed algorithm could successfully detect rotated faces, and was robust to rotation, low light level conditions and complicated backgrounds. In future research, a color correction will be incorporated to improve the detection rate in a range of environments.

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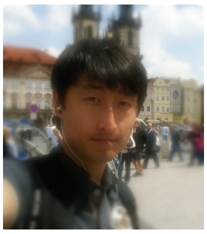

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