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A Novel Side Face Contour Extraction Algorithm for Driving Fatigue Statue Recognition

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ABSTRACT Fatigued driving detection, which employs pattern recognition to discover the state of a driver's fatigue, is considered a key technique to improve road safety. However, the widely used frontal face recognition systems have problems, such as low recognition accuracy, poor real-time ability, and highly complex algorithms. In this paper, a new color space modeling, which uses multi-threshold decision criteria, is used to enhance facial skin extraction performance, and a three-step strategy is designed to eliminate noise and other adverse effects. Experiments show that the proposed algorithm can extract side face contour lines effectively and provide a scientific basis for real-time tracking of fatigue.

INDEX TERMS Face detection, side face contour, color model, face profile extraction.

I. INTRODUCTION

Road safety is a 'grand challenge' for a modern industrial society with close to a billion vehicles on the road today that are projected to double over the next 20 years. Traffic accidents take tens of thousands of lives each year, outnumbering deadly diseases or natural disasters [1]. The increasing number of traffic accidents due to a driver's diminished vigilance level has become a serious problem. A number of studies have shown that driver drowsiness is one of the major causes of road accidents, and driver hypo-vigilance related accidents always lead to severe injuries and losses.

Therefore, researchers are committed to develop new techniques to detect fatigued driving and suggest corresponding alarm methods. The design of a fatigued-driving detection system is based on identifying variables relating to the fatigue level of drivers. Face detection, which detects the presence and subsequently the position of a face, is the first step in automated facial image analysis. It is generally accepted that pattern recognition is an effective measure to detect fatigued driving, while related techniques, such as face location detection [2] and eye detection [3], are considered key issues in this field of research.

A video camera is useful in detecting driver drowsiness symptoms, such as yawning, eye closure, eye blinking, head poses, etc. The mainstream driving fatigue detecting methods focus on eye, mouth and head posture from frontal images. The major challenge in face detection is the wide variations in the facial patterns caused by factors such as lighting, orientation, size, expressions and ethnicity. The presence of complex backgrounds or facial features, such as glasses, beards, and moustaches, also adds to complexity. The variations of frontal face images caused by ambient illumination are even greater than the variations of facial images of different people [4].

To overcome the issues with frontal fatigue detection, researchers feel that side face contour detection is an effective approach. Unlike frontal image detection, side face contour detection focuses on the relationship between facial profile and driver fatigue instead of facial status and makes a decision based on the profile change of nose, mouth and chin. Therefore, we need to distinguish skin-color areas from complex background images and extract a contour line. Two key points are involved. One is skin color modeling; the other is noise removal technique.

In this paper, a new color space modeling, which uses multi-threshold decision criteria, is used to enhance facial skin extraction, and a three-step strategy is used to eliminate noise and other adverse effects.

The rest of the paper is organized as follows. Related works are analyzed in Section II. Section III describes basic definitions of several common color spaces. In Section IV, the proposed side face recognition method is described in detail, and image processing effects are exhibited. In Section V, conclusions and further work are presented.

II. RELATED WORK

Fatigued driving detection is a significant research area in modern intelligent transportation systems. Face recognition is considered a key point and attracts researcher attention.

Previous work covers key points of face recognition, such as frontal face algorithms, side contour extraction techniques, and skin color modeling.

As one of the mainstream methods, a knowledge base algorithm is a means to achieve frontal face recognition. Yang and Huang et al. proposed a knowledge division level based face detection method in which a three-layer system is defined to fulfill feature filtering, equalization and ruler detection [5]. Knowledge base is the major factor influencing performance of all knowledge based methods. Detection accuracy in the literature [6] is relatively low. However, this method provided a viable basic solution, from which a number of improved algorithms are derived.

Feature based methods are considered effective for frontal face recognition. Scientists are devoted to finding algorithms to distinguish facial features such as outline, eyes, nose, mouth, jaw, etc. The face outline position is the first step of recognition. Employing a Canny operator, Canny John presented a method to extract image edges from a complex background [7]. A heuristic search method is used to revise the edge line. In the literature, [8], a geometric features oriented algorithm is presented. There are two stages to this algorithm: face coarse position by boundary detection and fine position based on a CART (Classification And Regression Tree) algorithm [9]. In addition to face outline position, facial features are important in driver fatigue detection. To better recognize facial features, scientists have developed several methods, such as image feature vector based, PCA (Principal Component Analysis), K-L transform [10], neural network, and support vector machines [11]. Yow and Cipolla proposed a vision features extraction method, in which an eigenvectors mean and covariance matrix is constructed based on training facial feature data [12]. In 2015, Kohonen put forward a face recognition method, which employs a feature vector to construct an autocorrelation matrix, while a neural network is used to calculate a normalized vector of the detected image [13]. Rowley presented a neural network based face detection method [14] in which all images are pretreated with multiple constraints before being sent into the neural network. Some mixed approaches are presented. Literature [15] combined PCA and Hotelling transform, while Reddy [16] combined PCA and neural network to detect the human face.

Side face recognition techniques rely on geometric feature identification. Fleuret and Geman [17] proposed a novel detection algorithm for objects with a complex pose where it is possible to train pose specific classifiers without clustering the data. Canny John's image edge extraction method [7] is effective in side contour recognition. S. C. Cheng [18] presented an automatic facial expression recognition system that utilizes a semantic based learning algorithm using the analytical hierarchy process that could be used in side face contour extraction. Han Tao [19] believes that the Fractal and Fourier description should work well in side face recognition and presented a side face features extraction algorithm. In this paper, a geometric features identification method is used to extract side face contour.

Skin color modeling is another key technique for face recognition. Jones and Rehg believe a histogram model, which shows advantages in recognition accuracy with low computational cost [20], is a good approach. Their experimental results show that a histogram algorithm achieves a detection rate of 80% with 8.5% false positives. Rein-Lien Hsu et al. employed skin color features [21] to realize face location. Most of the existing skin color models are established on chrominance planes [22]–[24]. By analysis and comparison of the chrominance of different colors, the skin color area can be distinguished from non-skin colors. Unfortunately, the chrominance based method only performs well under medium luminance conditions. Both low and high luminance could make the boundary between skin and non-skin areas hard to distinguish. To solve this problem, Hsu et al. [25] suggested a non-linear transform to the YCbCr color that makes the skin color cluster in the chrominance plane luma-independent. Garcia and Tziritas used a set of bounding planes to approximate the skin clusters in YCbCr and HSV spaces [26]. Based on YCbCr color space related method, in this paper, a new color space model, which uses multi-threshold decision criteria, is used to enhance facial skin extraction performance. Color correction and mathematical morphology are used to enhance the extractive effect.

III. COLOR SPACE

In-car images have a relatively complex background, low contrast and insufficient brightness, which usually decreases fatigue detection and recognition. The most popular approach to face localization is the use of color information, whereby estimating areas with skin color is often the first step. It is important how the face area is separated from a complex background.

Color space, which expresses color in a mathematical method, is a specific organization of colors. The common color spaces include RGB, HSV, HSI, YCbCr, CIE-Lab, and CIE-Luv.

A. RGB COLOR SPACE

RGB is characterized as a basic color space, in which different proportions of three primary colors: red, green and blue (RGB), produce a variety of colors. The progress is illustrated as

$$C(c) = R(r) + G(g) + B(b)$$

where r, g, b show the proportion of corresponding colors.

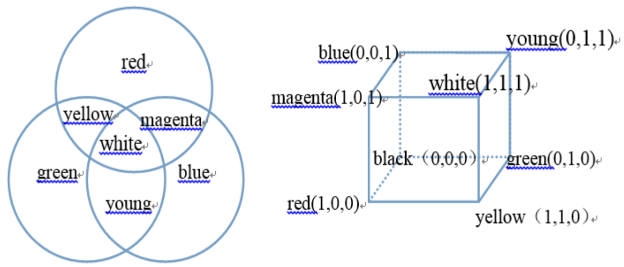


FIGURE 1. **RGB color space model.**

The basic RGB color space is shown in Fig. 1.

Skin color contains more red color component. The face area detection method always employs a normalized RGB color space as follows.

$$\begin{bmatrix} r \\ g \\ b \end{bmatrix} = \begin{bmatrix} \frac{1}{R+G+B} & 0 & 0 \\ 0 & \frac{1}{R+G+B} & 0 \\ 0 & 0 & \frac{1}{R+G+B} \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

where r, g, b is the R, G, B normalized after the new color component. The normalized process reduces the three-dimensional RGB space into a two-dimensional r-g space.

B. YCbCr COLOR SPACE

YCbCr color space, in which Y refers to Luminance, Cb refers to Chromatic blue and Cr refers to Chromatic red, is described as an orthogonal color space. It shrinks the redundancy present in the RGB color space and displays the components as statistically independent. The conversion from an RGB color space to YCbCr color space can be determined by using equation (2).

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.2290 & 0.5870 & 0.1140 \\ -0.1687 & -0.3313 & 0.5000 \\ 0.5000 & -0.4187 & -0.0813 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{2}$$

To meet the requirements of digital system processing, the YCbCr space is always revised by adding a 128 offset, as shown in equation (3).

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.2290 & 0.5870 & 0.1140 \\ -0.1687 & -0.3313 & 0.5000 \\ 0.5000 & -0.4187 & -0.0813 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 0 \\ 128 \\ 128 \end{bmatrix} \tag{3}$$

C. YUV AND YIQ COLOR SPACE

YUV color space is a color space for a TV system. In YUV color space, Y represents luminance, and U and V are chrominance signals. Each color has a corresponding chrominance signal vector, a Ch vector, to represent the phase of color saturation. The conversion from RGB color space to YUV color space can be determined by using equation (4).

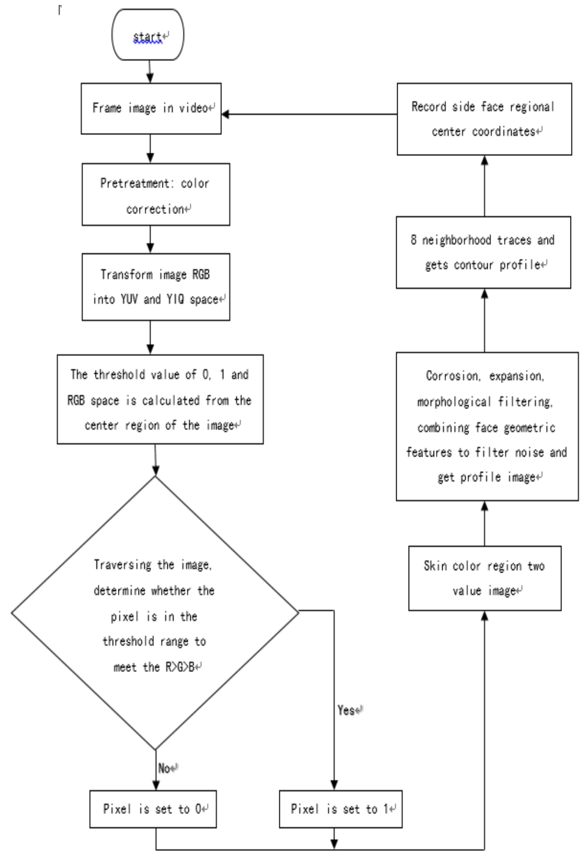


FIGURE 2. **Flow chart of the proposed algorithm.**

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.2999 & 0.587 & 0.114 \\ -0.147 & -0.289 & 0.436 \\ 0.615 & -0.515 & -0.100 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$
$$\theta = \tan^{-1}\left(\frac{|V|}{|U|}\right) \tag{4}$$

Due to its invariant feature, skin color has a regional distribution character in the color space. On the U-V plane of YUV color space, color tone ranges between red and yellow; its phase value is in the range of 100 to 150.

In YUV space, the phase feature can effectively remove background that is different than skin color. However, if the background is a skin-like color, it will not work. Rotating a UV component within thirty-three degrees could obtain an IQ component and construct YIQ space, which could solve the skin-like background separation problem. The conversion from RGB color space to YIQ color space can be determined using equation (5).

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.523 & 0.312 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{5}$$

D. COLOR SPACE MODELING

Combining YIQ and YUV, we obtain a color space model. Both component I of YIQ space and phase θ of YUV space can be used as criteria of skin color recognition. Previous work suggests the criteria range setting of $\theta \in [100, 150]$ and $I \in [20, 90]$. We have to convert the original image into YIQ and YUV space and determine if the I and θ values will stay within the fence and then recognize skin color.

In this paper, a multi-threshold combined decision method is proposed. Based on color modeling methods, four thresholds from I and θ are defined. The proposed method is described in detail in section IV.

IV. PROPOSED SIDE CONTOUR EXTRACTION ALGORITHM

In this paper, a side contour extraction algorithm is proposed.

A. FLOW CHART OF THE PROPOSED ALGORITHM

A flow chart of the proposed algorithm is shown in Fig. 2.

As shown in Fig. 2, the proposed algorithm involves three steps.

Step 1 (Side Face Basic Extraction): In-car cameras capture a large portion of a driver's image. To obtain the side face contour line, we extract the side face, including the face and neck, from the background. The basic extraction process, whose output is a two-value image, is based on skin color detection.

Step 2 (Extracted Side Face Correction): In this step, corrosion and expansion processing correct the two-value image of Step1.

Step 3 (Side Face Contour Line Extraction): Based on a corrected side face image, a side face contour line extraction process is performed.

B. SIDE FACE BASIC EXTRACTION

The goal of side face extraction is to obtain a side face contour line. During this phase, color correction and skin color modeling are performed.

- Color Correction

We assume that the mean values of the three components of the RGB in the image are similar to the same gray value, and they are limited in the range of [0 to 255] so that the adjustment of the RGB image of the three components is close to A_{aver}.

To reduce the impact of illumination, a color correction procedure is the first step of the proposed method. We follow Gray World's color equalization method [27] to remove color bias. The process is as follows:

1) *Extract the three components of RGB from the original image;*
2) *Calculate the mean value of the RGB components, denoted as R_{aver}, G_{aver} and B_{aver} respectively;*
3) *Calculate the average gray value as;*

$$A_{aver} = \frac{R_{aver} + G_{aver} + B_{aver}}{3} \tag{6}$$

4) *Calculate the gain coefficient for all three components of RGB;*

$$\begin{cases} K_r = \dfrac{A_{aver}}{R_{aver}} \\ K_g = \dfrac{A_{aver}}{G_{aver}} \\ K_b = \dfrac{A_{aver}}{B_{aver}} \end{cases} \tag{7}$$

5) *Reconstruct RGB components R', G', B' as;*

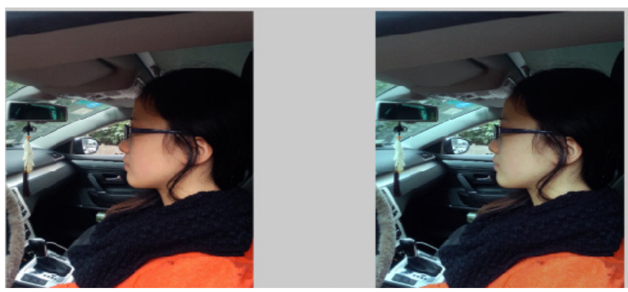
$$\begin{cases} R' = R^* Kr \\ G' = G^* Kg \\ B' = B^* Kb \end{cases} \tag{8}$$

6) *Restrict the value range of R', G' and B'. The value range of the reconstructed RGB components is set as [0, 255];*

$$\begin{cases} R' = 255, & R' \geq 255 \\ R' = 0, & R' \leq 0 \\ R' = R', & 0 \leq R' \leq 255 \end{cases}$$
$$\begin{cases} G' = 255, & G' \geq 255 \\ G' = 0, & G' \leq 0 \\ G' = G', & 0 \leq G' \leq 255 \end{cases}$$
$$\begin{cases} B' = 255, & B' \geq 255 \\ B' = 0, & B' \leq 0 \\ B' = B', & 0 \leq B' \leq 255 \end{cases} \tag{9}$$

7) *Rebuild the image color.*

This process is shown in Fig. 3.



(a) (b)

FIGURE 3. Color correction. (a) Before correction. (b) After correction.

As shown in Fig. 3, the correction process leads to a better color balance.

- Skin Color Modeling

Skin color modeling is the core step for side face region extraction. As the basis for model establishment, color space should be selected first. In this paper, the YUV and YIQ color spaces are used. Multiple threshold values criterion is used to construct the skin color model. The process is as follows.

1) *Transform the RGB values into YUV space and obtain Y, U and V values;*

$$\begin{aligned} Y &= 0.299^*R + 0.587^*G + 0.114^*B \\ U &= -0.148^*R - 0.287^*G + 0.437^*B \\ V &= 0.615^*R - 0.515^*G - 0.100^*B \end{aligned}$$

2) *According to the basic skin color decision rule, $U < 0$ and $V > 0$, Calculate value θ as*

$$\theta = \tan^{-1}|V/U|$$

3) *Transform the central block from RGB into YIQ space and record the value I;*

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.523 & 0.312 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

4) *Calculate both the mean and standard deviation of θ and I, denoted as $\theta_{\min}$, θ_{std}, I_{mean}, I_{std},*
5) *Obtain four threshold values of θ and I as follows:*

$$\begin{cases} YIQ_{\max} = I_{mean} + 3^*I_{std} \\ YIQ_{\min} = I_{mean} - 3^*I_{std} \end{cases}$$
$$\begin{cases} \theta_{\max} = \theta_{mean} + 3^*\theta_{std} \\ \theta_{\min} = \theta_{mean} - 3^*\theta_{std} \end{cases} \tag{10}$$

6) *Normalize R, G and B values and obtain R_{base}, G_{base}, B_{base},*

$$\begin{aligned} R_{base} &= \frac{R}{base + 0.5} \\ G_{base} &= \frac{G}{base + 0.5} \\ B_{base} &= \frac{B}{base + 0.5} \end{aligned}$$

where $base = R + G + B$;

7) *Calculate the mean value and variance of base, denoted as $base_{mean}$ and $base_{std}$;*
8) *Calculate the decision threshold of RGB space as*

$$base_{\lim} = -45.26 + 0.79 * (base_{mean} - base_{std})$$

9) *Convert the image into YUV and YIQ color space* Obtain three components U_p, V_p, I_p of the object pixel point p. Estimate the skin color region and calculate the corresponding phase P_{θ}. Make decision whether point p is a skin point. The two-value image of the skin color region is obtained by

$$\begin{aligned} &\text{IF} \begin{cases} YIQ_{\min} < I_p < YIQ_{\max} \\ \theta_{\min} < \theta_p < \theta_{\max} \\ R > G > B \end{cases} \\ &\text{OR} \begin{cases} 0.35 < R_{base} < 0.5 \\ 0.31 < G_{base} < 0.7 \\ base > base_{\lim} \end{cases} \\ &\text{THEN} \quad P = 255 \\ &\text{ELSE} \quad P = 0 \end{aligned} \tag{11}$$

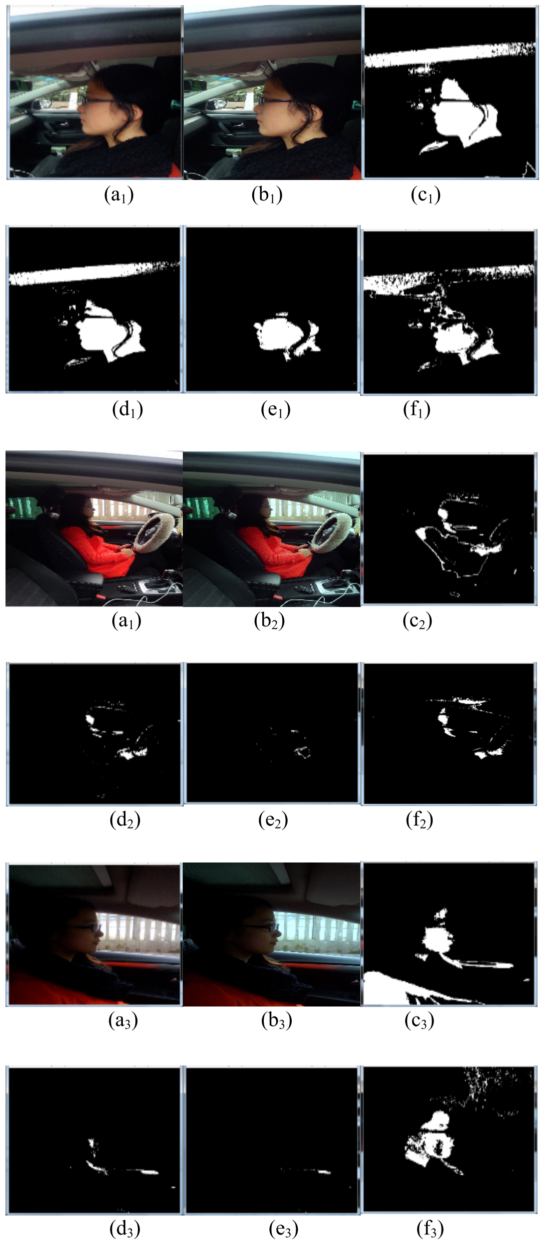


FIGURE 4. **(a) is the original image; (b) is the color correction image (c) is the Gaussian model of skin color detection results; (d) is an elliptical model of skin detection results; (e) is the YCrCb single threshold detection results; (f) is the proposed algorithm detection results.**

Here, three typical images, which are a near image with good light conditions, a remote image with poor face area luminance and a near image with bad light, are selected to verify the performance of the proposed multi-threshold combined decision model. The YCrCb threshold segmentation algorithm, Gaussian model and elliptical model are used as contrast object methods.

All experiments are based on the same pretreatment process, and the experimental results are shown in Fig. 4.

As shown in Fig. 4 (c_1, c_2, c_3), the Gaussian model can recognize skin color areas of all three typical images. However, the false detection probability of a no-skin area is

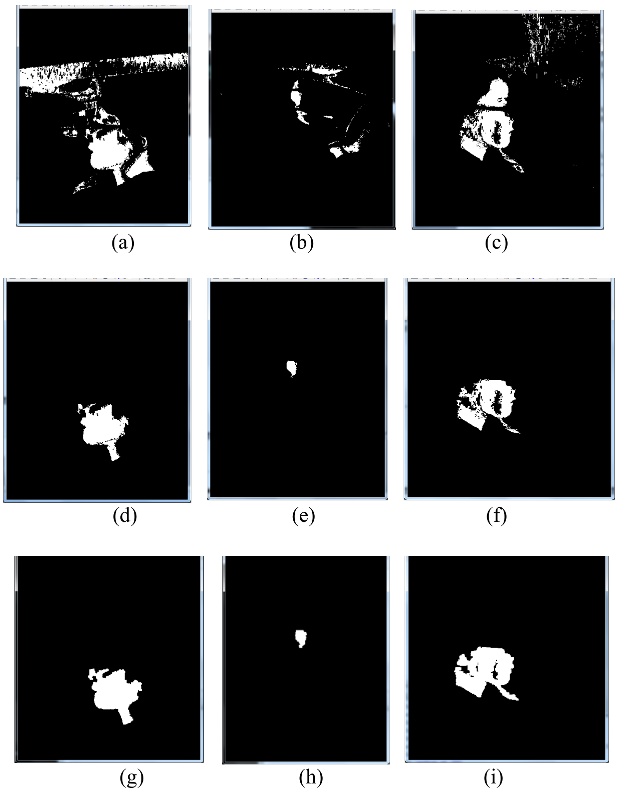


FIGURE 5. **(a-c) are the original binary image; (d-f) are the results for maximum area preservation; (g-i) are the results for expansion.**

also high. An Elliptical model can distinguish a large skin area under good light condition (Fig. $4d_1$); its processing performance for remote images with poor face area luminance is tolerated (Fig. $4d_2$) but fails to identify skin area under bad light (Fig. $4d_3$). The YCrCb threshold segmentation algorithm recognizes large skin color areas well under good light conditions (Fig. $4e_1$). On the other hand, as shown in Fig. 4 (e_2, e_3), its processing effect for bad luminance images is poor. Compared with all the contrast object methods, the proposed method can precisely detect the side face region of all three images. However, skin-like blocks and no-skin blocks could be observed. The experimental results provide solid empirical evidence on the efficiency of the proposed method.

C. SIDE FACE BASIC EXTRACTION

The proposed skin color modeling method is used to separate skin areas from a complex background. As shown in Fig. 4, the images include some non-skin points, which are considered noise and should be removed by further processing. The approaches for noise removal include a texture-based method and a mathematical morphology-based method. Many experts believe that the latter is effective in irrelevant noise elimination and useful in image data simplification. In this paper, mathematical morphology uses structural elements to measure and extract the corresponding shape in the image and then analyze the image. Two processes, corrosion and expansion, are performed.

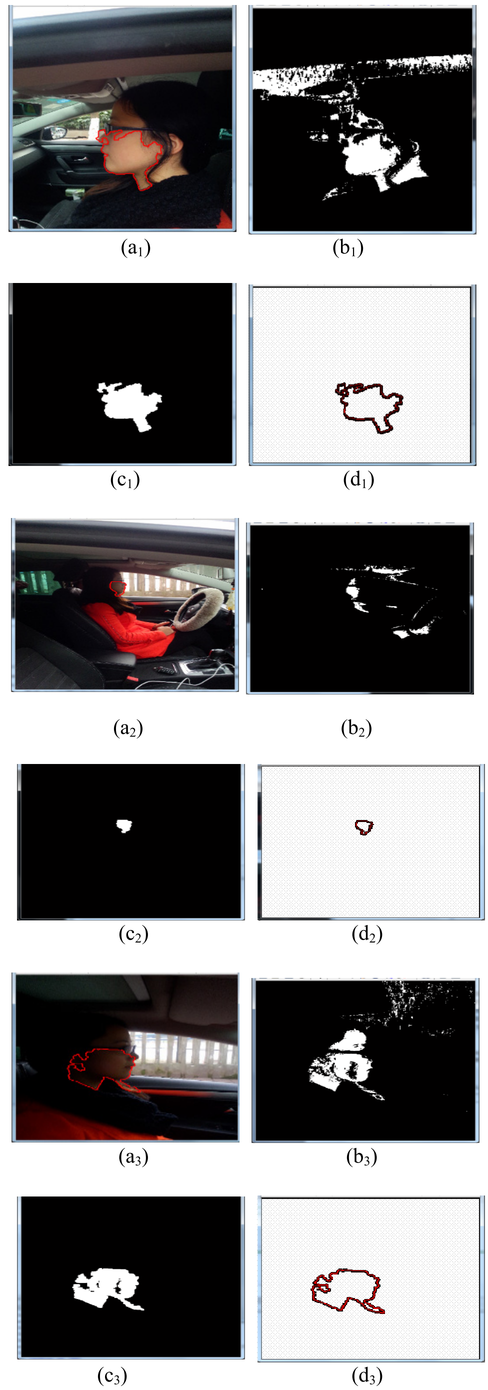


FIGURE 6. **(a) is a contour original image; (b) is profile two value image; (c) is the side face region extraction; (d) is a contour line extraction.**

Corrosion, which shrinks all points in the subset X+Y to X, is used to reduce target scope, enlarge inner holes in connected domains and eliminate isolated noise points. It is a filtering process, which removes image detail from a two-value image. The inverse process of corrosion, expansion, expands all points in X to X+Y and increases and coarsens the two-value image to fill inner holes and connect separate domains in the image.

The process is as follows.

1) *Repeat the corrosion process multiple times. Small details are removed and connected domain blocks become more clear;*
2) *Extract the side face features from the connected domain pictures. Calculate the ratio A and ratio B as;*

$$A = \frac{m}{n}, \quad B = \frac{area}{areq_{sq}}$$

3) *Make decision criterion as follows*

$$IF\ A > 3||A < 0.5||B < 0.3, \quad THEN\ L(i, j) = 0$$

4) *Calculate the area of each connected region, reserve only the largest area of the connected regions, and process the expansion and erosion of the extraction region to get a clear side face contour.*

This process is shown in Fig. 5.

As shown in Fig. 5, the side face region has been confirmed after the processes of corrosion, detection of the geometric features of the face, and expansion. The number of iterations of corrosion and expansion is determined by the experimenter.

D. FACIAL CONTOUR EXTRACTION

After precisely positioning the side face region, the face contour line extract process is performed. A face contour line extract method is proposed as follows.

1) *Construct a direction bias matrix. In this paper, we employ matrix Direction=[−1 1;0 1;1 1;1 0;1 −1; 0 −1;−1 −1; −1 0].*
2) *Find the position of the first white pixel near the upper left corner of the middle position of the image. Set it as the starting point of the boundary.*
3) *Search for each contour point from the starting in a clockwise direction by a pre-defined 8-neighborhood matrix until return to the starting point. Record the coordinates that have been found for each point of the boundary to a chain table in the order of the search.*
4) *The coordinate information stored in the chain table is extracted and connected in order, and the profile curve of the target is obtained.*

This process is shown in Fig. 6.

As shown in Fig. 6, a clear and complete contour is obtained. Inner holes in the connected region are removed and noise is eliminated. The proposed method involves no hole-filling process, which causes high computation complexity.

V. CONCLUSION

Because of the current number of traffic accidents and the many disadvantages of facial recognition algorithms, this paper presents a method of facial profile extraction.

A three-step strategy is designed to extract side face contours, and a new human skin color model based on multi-threshold combined decision is proposed.

A series of experiments are carried out to examine the performance of the proposed method. Three typical images, which are a close image with good lighting, a remote image with poor lighting and a close image with poor lighting, are selected to verify performance of the proposed multi-threshold combined decision model. An YCrCb threshold segmentation algorithm, Gaussian model and elliptical model are selected as contrast object methods. Experimental results provide solid empirical evidence of the efficiency of the proposed method. Experiments for the three steps involved show that the proposed three-step strategy is more accurate than face recognition algorithms. The hardware requirements for all cases of lower recognition rate and error rate are suitable for a variety of complex backgrounds and brightness and provide a new method for driver fatigue judgment.

In future work, self-adaption of the side face extraction process should be considered, and the use of shape and luminance information in removing false detection should be examined.

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