

Hand Segmentation for Hand-based Biometrics in Complex Environments

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Abstract—Hand-based biometric techniques, such as the ones based on palmprint, hand vein and hand shape, is becoming more important because of their convenience and high performance. Hand segmentation is one of the most important steps in these techniques. It is a challenge task to accurately segment hand in complex environment because of the complex background, varying illuminance and other unexpected interference factors. This paper proposes a novel approach to segment hand in complex environment using color and boundary information. In the proposed approach, the hand skin color model (HSCM) is firstly constructed by using artificial neural network (ANN). Then the HSCM is used to generate a probability map (PM) and the hand is roughly segmented from the complex background by thresholding PM. After that, the hand boundary is extracted from the original image by edge detecting and voting techniques. Finally, the hand boundary is employed to cut the roughly segmented hand to get the final segmented hand. The experimental results show that the proposed approach can effectively segment hand in complex environment.

Index Terms—hand segmentation, complex environment, skin color model, boundary extraction

I. INTRODUCTION

Hand-based biometric techniques are becoming increasingly important because of their convenience and high performance. In recent years, researchers gradually focus their interests on contactless hand-based biometrics which have higher user friendliness than the traditional contact ones. One of the most important steps of such techniques is to segment hand from complex scenarios with uncontrolled background, various lighting conditions, and unrestricted hand poses.

Hand segmentation from complex scenarios has long been an active research area in computer vision. It can be implemented in both videos and static images. The advantage of hand segmentation in videos is that the motion information can be integrated into the segmentation, and some successful tracking algorithms can be applied. Lee segmented hands from videos through frame difference for gesture recognition [1].

Ribeiro made a study on hand segmentation from videos by using the Gaussian mixture model (GMM) [2] to model the background pixels [3]. Hand segmentation from videos has been successfully used in gesture recognition, sign language, human computer interactions (HCI), robot control, etc. Hand-based biometric applications require a steady hand pose for feature extraction, and hence most hand-based biometric methods are performed on static images. Hand segmentation from static images can be roughly categorized into color-based and appearance-based methods.

Color-based method is one of the most frequently used methods in segmenting skin-colored objects in color image. It usually constructed a skin color model in a specific color space using parametric or non-parametric classifiers. Based on the learnt skin color model, each pixel in an image is classified as a skin-pixel or not. Color-based segmentation has been successfully employed in face detection. Chaves-González performed a performance evaluation on face detection over various color spaces [4]. They used the k-means algorithm as the classifier, and in their experiments, the HSV space provided the best result. Jones used a large dataset as the training data to establish a GMM for skin classification [5]. Their experiments demonstrated that there existed a significant degree of separability between the skin and non-skin distributions. Pham proposed to detect hands from complex background for HCI [6]. They also trained a GMM in the LUV color space neglecting the luminance part, and segmented hands by incorporating stereo information. Lee performed skin color detection using their proposed elliptical boundary model [7]. Their experiments in six chrominance spaces outperformed the single Gaussian model and the GMM. Yin developed a hand segmentation method for robot control based on restricted coulomb energy (RCE) neural network, and claimed that the HSI and $L^*a^*b^*$ color spaces are more suitable for hand segmentation than the RGB color space [8]. Besides, Jedynak considered three models in their work for skin detection, including the baseline, Hidden Markov, and the color gradient [9]. Brand performed a performance evaluation of three different methods for skin detection [10].

Appearance-based methods extract appearance features of hands (shape, texture, intensity, etc.) in gray scale

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images for classification. Ong presented an unsupervised approach for hand detection and hand shape recognition by using a two-layered boosted hand detectors tree [11]. Caglar detected hands by exploiting the geometric properties of the finger edges and fingertips [12]. Nguyen [13], Kolsch [14], and Zondag [15] respectively proposed to employ Ada-boost algorithm to detect hands from complex background. By using the concept of integral image, the detection is very efficient and it is sufficient for real-time applications. Recently, Song [16] proposed a method for detecting and tracking moving hand based on hand edge. Feng [17] established 3D hand model for human hand detection and tracking.

Besides, combinations of multiple features can be used to promote the hand segmentation accuracy. Mittal integrated color-based and appearance-based methods for hand segmentation, and achieved accuracy much higher than any single method [18].

In hand-based biometrics, such as palmprint and hand shape recognition, accurate detection of key points is required for precise region of interest (ROI) extraction. The detection of key points relies on the tracing of hand boundaries. Hence, clear and accurate hand boundaries are required in hand segmentation. However, most existing hand segmentation algorithms from static images focus on segmenting a hand region without precise hand boundaries. Thus, they are not preferred in hand-based biometrics. This paper proposes a hand segmentation method from complex scenarios, which combines skin color model and boundary information.

The remainder of this paper is organized as follows: Section 2 gives an overview of the framework of the

proposed approach; Section 3 describes the construction of skin color model; Section 4 presents the procedure of rough hand segmentation; Section 5 provides the refinement of the segmentation using boundary vote map and boundary cutting; Section 6 demonstrates the experimental result and proposes a new evaluation criterion, and then makes some discussion and comparisons; and finally, we conclude the whole work in Section 7.

II. FRAMEWORK OF THE PROPOSED APPROACH

The framework of the proposed method is depicted as Figure 1. The proposed approach is composed of three stages: hand skin color model (HSCM) construction, rough segmentation and fine segmentation.

At the HSCM construction stage, the HSCM is constructed by using a four-layered back propagation (BP) ANN. Each pixel in an image is classified by the ANN as skin or non-hand skin.

At the rough segmentation stage, a probability map (PM) of hand image is firstly generated by using the HSCM, and then the hand is roughly segmented from the complex background by binarizing PM.

At the fine segmentation stage, the hand boundary is extracted from the original image by edge detection in various color channels to obtain redundancy hand boundary information. A voting method is proposed to get a final hand boundary from the multi-color-channel edges. Finally, the hand boundary is employed to cut the roughly segmented hand to get the final segmented hand.

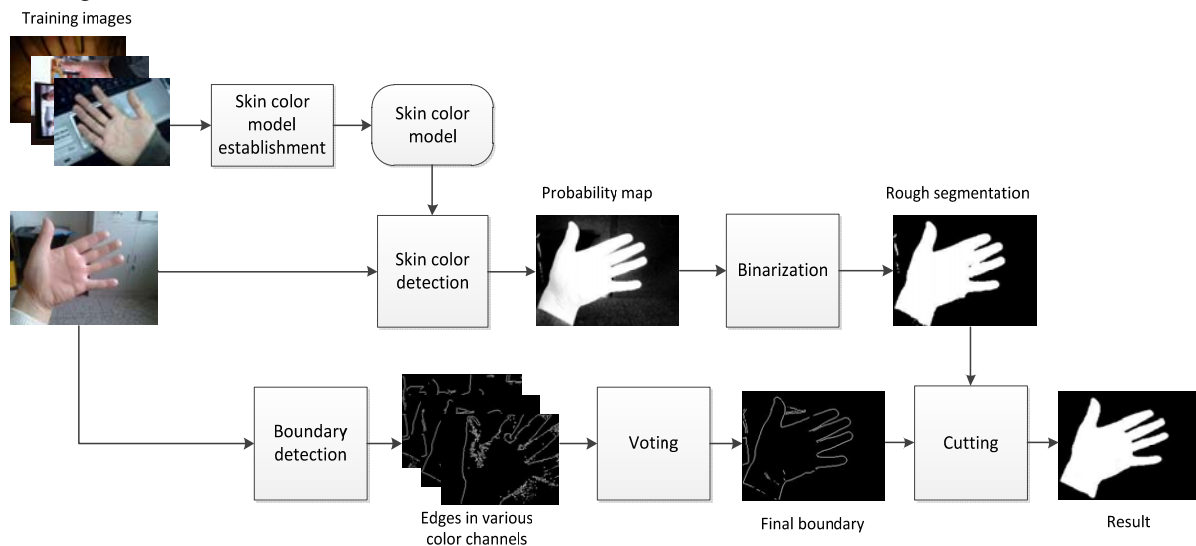


Figure 1. The framework of the proposed approach.

III. HSCM CONSTRUCTION

Skin color has been proven to be robust information for hand detection and tracking [20]. Hand skin color model is a classifier which can be used to classify each pixel in an image as hand skin or non-hand skin.

Let I denote the original image. Each pixel in I can be represented with different color space, such as RGB and $L^*a^*b^*$, etc. The different channels of the different representations of the image reflect different property of the image. This work uses the normalized R, G, B channels in RGB color space and a^* , b^* channels in CIE $L^*a^*b^*$ color space to represent each pixel of the image. That is, the feature vector V of the pixels in the image are defined as Equations (1)-(3).

$$V_1 = \left[\frac{R}{R+G+B}, \frac{G}{R+G+B}, \frac{B}{R+G+B} \right] \quad (1)$$

$$V_2 = \left[\frac{a^*}{L^*+a^*+b^*}, \frac{b^*}{L^*+a^*+b^*} \right] \quad (2)$$

$$V = [V_1, V_2] \quad (3)$$

We will use the feature vectors to train the HSCM. In this paper, a four-layered BP neural network is used to construct the skin color model. The number of input neurons is 5. Both of the two hidden layers have 32 neurons. And output layer has only one neuron, which gives the probability p of the input pixel to a skin pixel. The values of p range between $[0, 1]$. The larger the value of p is, the more likely the pixel is to be a skin pixel. The first and second hidden layer respectively has a transfer function of sigmoid and hyperbolic tangent. Figure 2 shows the structure of this ANN.

During the training of the HSCM, a set of training color hand images is used for training this ANN. As a supervised learning strategy, the pixels of the training images are labeled as skin or non-skin manually. The network is trained based on gradient decreased back propagation with momentum. When training, the input sequence of the images is random.

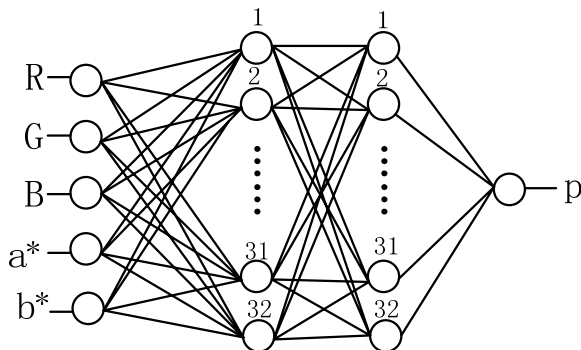


Figure 2. The structure of the ANN used in this paper.

IV. ROUGH SEGMENTATION

For the input image I , the feature vector of each pixel $I(i, j)$ is constructed and fed to the ANN. The output is denoted as $P(i, j)$. $P(i, j)$ ranges between $[0, 1]$, which describes a probability of a pixel is on hand. The larger $P(i, j)$ is, the more likely $I(i, j)$ is on hand. We name P as the probability map (PM) of the original image, as shown in Figure 4(b).

PM can be regarded as a gray scale image, in which high-intensity pixels correspond to skin-colored objects. Hand can be roughly segmented by binarizing PM with a threshold. Here we use entropic thresholding method to binarize PM.

Let P_i be the intensity of pixel i , $\bar{P}$ is the average intensity value of pixels of PM, i.e. $\bar{p} = (\sum_{i=1}^N p_i)/N$ where N is the number of pixels. The intensity values of all pixels in PM are amended using Equation (4) so that the average intensity value of PM is 0.5.

$$p'_i = \frac{0.5 \times p_i}{\bar{p}} = \frac{p_i}{2\bar{p}} = \frac{Np_i}{2\sum_{k=1}^N p_i} \quad (4)$$

Let f_i be the number of pixels in PM with value i , $i \in [0, M]$, and M the largest value of the PM. Probabilities of two pixel classes, i.e. background and foreground (hand) are denoted as $P_b(i)$ and $P_f(i)$. Entropies for background and foreground pixels are computed by Equations (7) and (8). $\bar{T}$ is the optimal threshold computed by criterion as Equation (9).

$$P_b(i) = \frac{f_i}{\sum_{j=0}^T f_j}, 0 \leq i \leq T \quad (5)$$

$$P_f(i) = \frac{f_i}{\sum_{j=T+1}^M f_j}, T+1 \leq i \leq M \quad (6)$$

$$H_b(T) = - \sum_{i=0}^T P_b(i) \log P_b(i) \quad (7)$$

$$H_f(T) = - \sum_{i=T+1}^M P_f(i) \log P_f(i) \quad (8)$$

$$\bar{T} = \arg \max_{0 \leq T \leq M} \{ \max_{T=0,1,\dots,M} \{ H_b(T) + H_f(T) \} \} \quad (9)$$

The time complexity of the algorithm is $O(M^2)$. While fast entropic thresholding algorithm [21] can achieve a $O(M)$ time complexity by calculating the renormalized part repeatedly.

To obtain a lower false negative rate, a lower threshold is needed for binarization. In this paper we apply a weight that less than 1 to $\bar{T}$, and get the final threshold by $T' = C \times \bar{T}$. For the selection of C , an experiment is carried out on a training dataset. Different values of C is applied and the segmentation is performed. The summation of false positive rate (FPR) and false negative

rate (FNR) of segmentation is taken as the criterion. The C value corresponding to the smallest FNR + FPR is taken as optimal as shown in Figure 3. In this work, the value of C is set as 0.8. Figure 4 demonstrates an exemplar result of rough segmentation.

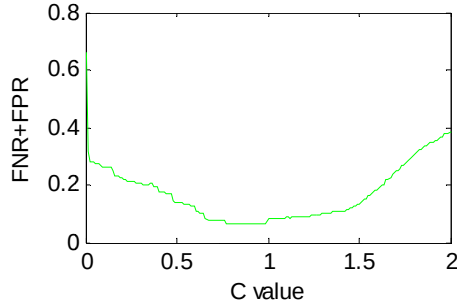


Figure 3. C value and correspondent performance



(a) Original image. (b) Probability map. (c) Rough segmentation.

Figure 4. Results of rough segmentation.

V. FINE SEGMENTATION

The fine segmentation is based on edge detection. The segmented hand is expected to have a continuous and complete boundary. However, most of the traditional edge detectors fail to get such an ideal boundary in case of noises. In this paper, we propose a hand boundary detection method based on boundary vote map (BVM), which combines the detected edges of more than one color channels to guarantee the completeness of hand boundary.

The Sobel edge detector is applied for edge detection in this work. Sobel detector tends to be more robust to noises and thus will be affected less by edge fracture.

The Sobel edge detector is applied on various color channels, and the results are shown in Figure 5. From Figure 5 we can observe that the detection performances are different over different color channels. The hand boundary is incomplete in each single color channel. If we combine the results of more than one color channel, we can expect to get a complete hand boundary. In this work, the combination is established through.

A. BVM Construction

Let Boolean value v_{ij} indicate whether i is an edge pixel on channel $j \in [1, C]$, where C is the total number of channels. We can then define v_i as the vote of pixel i indicating in how many channels i is an edge pixel, i.e. $v_i = \sum_{j \in C} v_{ij}$. The channels used for edge detection include: R, G, B of RGB space, Y, Cb, Cr of YCbCr space, and a^* , b^* of CIE $L^*a^*b^*$ space. This paper gives up L^* ($L^*a^*b^*$) and V (HSV), to avoid redundancy because Y (YCbCr), V, L^* all represent lightness and

also give up H, S (HSV) in which channels edge detection algorithm show unstable performance.

The voting process generates a gray-scale image whose intensity values indicate the probability of a pixel to be an edge pixel. To further decrease noise edges, a threshold 3 is applied in this paper for binarizing the BVM.

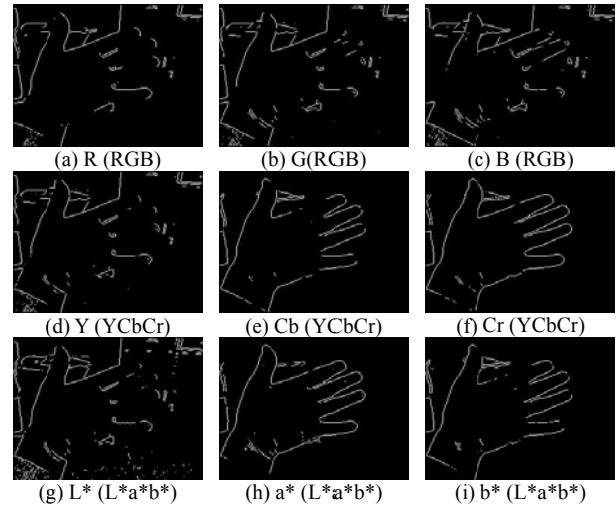


Figure 5. Sobel based edge detection on different channels.

B. Improvement of BVM

In BVM construction, only the edge pixels in each channel are selected for voting. As an improvement of this strategy, the scope of voting pixels is extended. The extended pixels are the neighborhood pixels of $v(x, y)$ whose distances to $v(x, y)$ are not larger than R . The strategy is shown in Figure 6, in which yellow blocks indicate the extended pixels from original edge (red blocks in Figure 6). Figure 7 shows the comparison of improved BVM and the original BVM. It can be seen that the improved BVM generates more complete and wider hand boundary.



Figure 6. Strategy of improved BVM ($R = 1$)

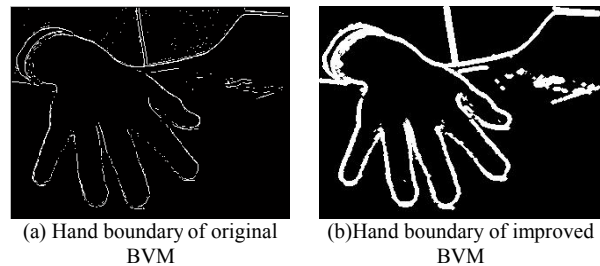


Figure 7. Improvement for BVM

C. Boundary Cutting

The extracted hand boundary is supposed to be a close curve. The foreground pixels outside the hand boundary detected by rough segmentation are considered to be non-

hand-pixels, and such pixels will be cut off by the hand boundary. Through this way, the rough segmentation is refined.

After segmentation refinement, the hand becomes a connective region and it is believed to be the largest region in the image. Finally, morphologic hole-filling operations are performed for post processing.

The process of hand segmentation can be described as Algorithm 1.

Algorithm 1. Hand segmentation

- i. Computing PM using ANN;
 - ii. PM amending according to average probability;
 - iii. Threshold determination using fast entropic thresholding technique and binarization;
 - iv. Building VM and VM binarization;
 - v. Boundary cutting;
 - vi. Post-processing;
-

VI. EXPERIMENTAL RESULTS

In this work, experiment is performed on a data set of 120 images with resolution 640*480. These images are acquired in various environments and lighting conditions, for example, simple environment with moderate light condition, complex environment, and dark environment with flash lamp exposure, etc. 40 of the images are taken as training set, and are used for training ANN and the weight C . First row of Figure 8 demonstrates some images from the dataset. Fifth row of Figure 8 shows the corresponding segmentation results, which are satisfactory compared with ground-truth (last row of Figure 8).

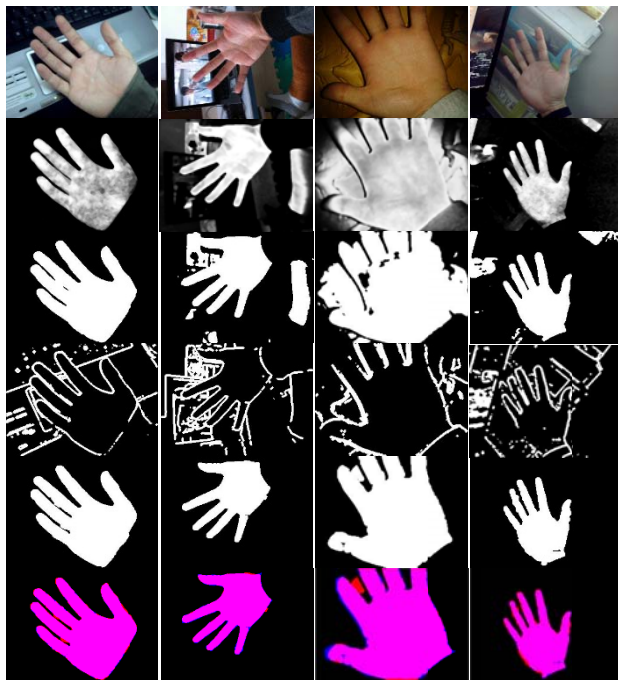


Figure 8. Segmentation results. First row: original images. Second row: HSCM images. Third row: binarized HSCM images. Fourth row: boundary images. Fifth row: segmentation results. Sixth row: ground-

truth.

A. Pixel Level Evaluation

At the pixel level, this paper utilizes sensitivity, specificity, positive predictive value and misclassified proportion to evaluate the segmentation, as shown in Equations (10)-(13).

$$\text{sensitivity} = \frac{NTP}{NTP + NFN} \quad (10)$$

$$\text{specificity} = \frac{NTN}{NTN + NFP} \quad (11)$$

$$\text{positive predictive value} = \frac{NTP}{NTP + NFP} \quad (12)$$

$$\begin{aligned} \text{misclassified proportion} \\ = \frac{NFP}{NTP + NFP + NTN + NFN} \end{aligned} \quad (13)$$

where NTP , NFP , NTN and NFN is the number of true positive, false positive, true negative, false negative instances, respectively. The segmentation results at pixel level are listed in Table 1.

TABLE 1.
SEGMENTATION RESULT AT PIXEL LEVEL

sensitivity	specificity	Positive predictive value	misclassified proportion
96.54%	96.92%	95.21%	1.89%

B. Image Level Evaluation

Image level evaluation consists of the evaluations of locating and segmentation.

Evaluation of Locating. In this paper, we define the location of a hand as the center of inscribed circle of the hand. The location of the segmented hand is denoted as $C_a(x_a, y_a)$, while the location of the manually marked hand is denoted as $C_m(x_m, y_m)$. The distance between C_a and C_m is taken the deviation of hand location. As normalization, the distance is divided by the radius of inscribed circle. R_m is the radius corresponding to C_m . d_L is the distance computed by Equation (14).

$$d_L = \frac{\text{dist}(C_a, C_m)}{R_m} \quad (14)$$

where

$$\text{dist}(C_a, C_m) = \sqrt{(x_a - x_m)^2 + (y_a - y_m)^2} \quad (15)$$

Evaluation of Segmentation. For segmentation evaluation, the Youden's index as Equation (16) is employed.

$$\text{Youden's index} = \text{sensitivity} + \text{specificity} - 1 \quad (16)$$

Image level evaluation is then performed using the combination of the two criteria, and the results are listed in Table 2. An image can be determined “well-located” and “well-segmented” by two thresholds that are respectively center distance and Youden’s index. The rate of well segmentation is shown in Figure.9.

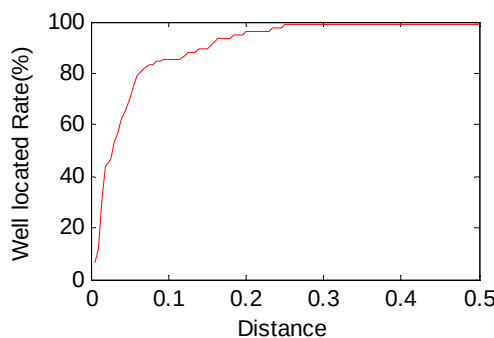
TABLE 2.
EXPERIMENTAL RESULT AT IMAGE LEVEL

Evaluation of Location		Evaluation of Segmentation	
Average distance	Standard deviation	Average Y.’s index	Standard deviation
0.0923	0.0118	0.9270	0.0025

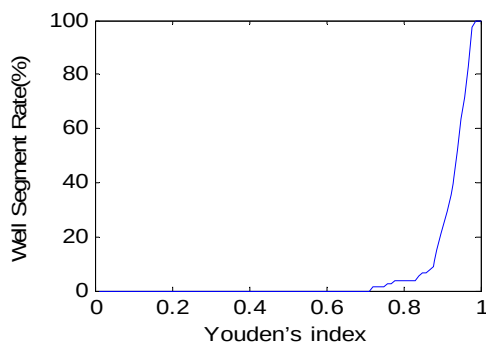
C. Discussion

From the experimental results, it can be seen that the proposed method can achieve prominent accuracies at both pixel level and image level. The results indicate that color information plays an important role and is effective in hand segmentation. The proposed BVM method can effectively refine the rough segmentation generated by color information.

Different color spaces and different combinations of color channels may lead to different results. As a comparison study, Table 3 lists the experimental results using different color spaces and different combinations of color channels as input of ANN to train HSCM. From the results we can see that the RGB color space is more effective for training the HSCM than other color spaces.



(a) Criterion - distance of inscribed circle center



(b) Criterion – Youden’s index

Figure 9. Evaluation at the level of image

Another comparison study is carried out to evaluate the performance of learning algorithms for constructing HSCM, and the results are listed in Table 4. The results show that compared with the considered algorithms, ANN gets a better performance despite the influence of complex environment.

Gaussian mixture model (GMM) is one of the most popular methods to build skin color model. As a comparison, this paper trains the Gaussian mixture model with the same training data set as used by ANN and evaluates under the same test data set. Table 5 lists the results of segmentation using GMM. The Results of GMM show lower sensitivity and higher specificity, which is because of high threshold when binarization. However, thresholding method for segmentation using GMM shares the same with segmentation using ANN. Figure 10 shows comparisons of PMs between segmentations using GMM and ANN.

Variable illumination condition is the most difficult problem in complex environment segmentation. The hand under exposure of the camera flash is well segmented using our algorithm (refer to Figure 8). However, the phenomenon of uneven lighting condition within the palm area remains troublesome. Besides, discoloration of hand area makes skin color model falsely refuse skin pixels.

TABLE 3.
DIFFERENT COLOR SPACE AND CORRESPONDING PERFORMANCE

Color space	sensitivity	specificity	Predictive value	misclassified proportion
L*a*b	95.31%	94.93%	92.25%	3.11%
HSV	78.35%	97.64%	95.47%	1.44%
RGB	93.35%	96.65%	94.64%	2.05%
RGB,HSV	88.18%	96.52%	94.14%	2.13%
HS(HSV), a*b*, CbCr	86.48%	83.19%	76.53%	10.29%
RGB, a*b*	96.54%	96.92%	95.21%	1.89%

TABLE 4.
PERFORMANCE OF DIFFERENT SKIN DETECTORS REPORTED BY THE AUTHORS

Method	Sensitivity	Specificity
Thresholding of I axis in YIO [10]	94.7%	69.8%
Bayes SPM in RGB [10]	93.4%	85.2%
Single Gaussian in CbCr [7]	90%	66.7%
Gaussian Mixture in IQ [7]	90%	70%
Elliptical boundary model in CIE [7]	90%	79.1%
Gaussian Mixture models in RGB [5]	80% 90%	90.5 84.5%

Bayes SPM in RGB [5]	80% 90%	91.5% 85.8%
SOM in TS [5]	78%	68%
Maximum Entropy Model in RGB [9]	80%	92%
The proposed method	96.64%	96.92%

TABLE 5.

SEGMENTATION PERFORMANCE OF GAUSSIAN MIXTURE MODEL AS SKIN COLOR MODEL

	sensitivity	specificity	Positive predictive value	misclassified proportion
HSV	50.85%	99.03%	97.07%	0.59%
RGB	64.49%	99.18%	98.02%	0.50%
L*a*b*	63.89%	99.17%	98%	0.51%
YCbCr	64.49%	99.18%	98.02%	0.50%
ANN+RGB +L*a*b*	96.54%	96.92%	95.21%	1.89%

VII. CONCLUSIONS

A novel approach to segment hand in complex environment using color and boundary information is proposed in this paper. In the proposed approach, the hand skin color model is constructed by using artificial neural network. Then the hand skin color model is used to generate a probability map and the hand is roughly segmented from the complex background by thresholding the probability map. The rough segmentation can effectively remove most of the non-skin-colored background objects. After that, the hand boundary is extracted from the original image by edge detection and voting technique. The voting technique combines various color spaces and hence can dismiss false positives and discontinuity of edges. Finally, the hand boundary is employed to cut the roughly segmented hand to get the final segmented hand. Experimental results show that the proposed method can achieve a relatively high sensitivity and specificity. The method can be applied for hand-based biometrics, and it is also suitable for various occasions requiring hand segmentation, for example, human machine interface, etc.

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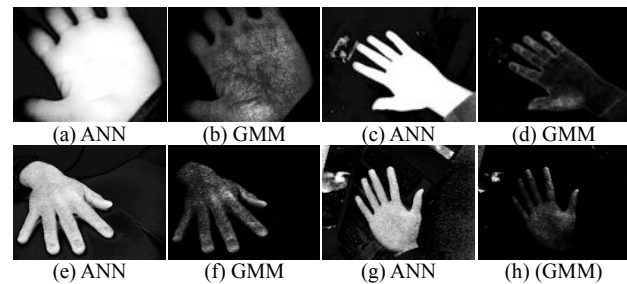


Figure 10. PMs produced by two different skin color model

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