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The Use of HSV Color Model for Subtle Ear Region Extraction

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Abstract

Identifying people by their ear has recently received import attention in the literature. The accurate segmentation of the ear region is vital in order to make successful person identification decisions. This paper presents an effective approach for ear region segmentation from color ear images. Firstly, the RGB color model was converted to the HSV color model. Secondly, thresholding was utilized to segment the ear region. Finally, the morphological operations were applied to remove small islands and fill the gaps. The proposed method was tested on a database which consisted of 105 ear images taken from the right sides of 105 subjects. The experimental results of the proposed approach on a variety of ear images revealed that this approach is efficient in segmenting ear images under various environments and it gave a detection rate of 98.61% for ear segmentation.

Keywords: Image segmentation; HSV color space; Ear extraction; Morphological operation.

أستخدام النموذج اللونيHSV لاستخراج منطقة الأذن الرقيقة

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الخلاصة

إن التعرف على الأشخاص من خلال الاذن قد حظي مؤخراً باهتمام كبير في الأدبيات السابقة. إن التجزئة الدقيقة لمنطقة الأذن أمر حيوي من أجل اتخاذ قرارات ناجحة لتحديد هوية الشخص. تقدم هذه الورقة طريقة فعالة لتجزئة منطقة الأذن من صور الأذن الملونة. أولاً ، تم تحويل نموذج اللوني RGB إلى نموذج اللونيHSV . ثانياً ، تم استخدام طريقه العتبة لتقسيم منطقة الأذن. أخيرًا ، تم تطبيق العمليات المورفولوجية لإزالة الجزر الصغيرة وملء الفجوات. حيث تم اختبار الطريقة المقترحة على قاعدة بيانات تتكون من 105 صورة أذن مأخوذة من الجانب الايمن ل 105 شخصاً. أظهرت نتائج التجربة المقترحة على مجموعة متنوعة من صور الأذن ، أن هذه الطريقة فعالة في تجزئة صورة الأذن في بيئات مختلفة وأنها أعطت معدل اكتشاف بنسبة 98.61٪ لتجزئة الأذن.

Introduction

As a biometric, ear of human holds a number of desired qualities including uniqueness, permanence, and universality [1], and it offers individual features for a person

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identification/verification [2]. Automatic ear segmentation from the collection of color images becomes a major stage with high effects on the subsequent recognition/ verification tasks [3-4].

In recent years, many different ear segmentation methods have been published. Prakash, et al., 2009, [5] presented a novel technique of automatic ear segmentation. The presented mechanism was based on hierarchical clustering and segmenting of the ear by using the edge information; first, skin segmentation was performed, then the hierarchical clustering was utilized to obtained edges, followed by the utilization of the obtained clusters to localize the ear. Their method was tested on IIT Kanpur Database and achieved an accuracy value of 94.6%.

Kumar, et al., 2012, [6] proposed a method for automated ear segmentation using combinations of Fourier descriptors and morphological operations. At first, they used a Gaussian filter in the input image for suppressing noise, then they utilized histogram equalization, followed by the application of the Otsu's threshold to generate a binarized mask image. Thereafter, they applied the opening and closing morphological operations on the binarization of the image to eliminate the noise. The proposed method was tested on the ear image dataset of 125 subjects.

Vélez, et al., 2013, [7] proposed a method to detect ear which combines the circular Hough transform with anthropometric ear proportions. First, the color image was converted into greyscale, and then the median filter was applied. After that, a Canny edge detector was utilized for obtaining a binary edge image. Then, an inversion of the binary edge image was applied, followed by the use of mathematical morphology processing to remove small regions. Finally, the ear region extraction was performed by applying the circular Hough transforms. Their proposed method was evaluated on three different image databases and achieved an accuracy of ear detection on the colored image of 78.33 %.

Yousif, et al., 2015, [8] presented a method for the extraction of ear region using color-based segmentation method. Initially, skin segmentation was performed using HSV color space, followed by extracting the range rule to the obtained skin color area. After that, the median filter was applied for noise removal. Finally, unnecessary parts were removed and the ear clip was extracted. The presented method was tested on different images and achieved an accuracy of segmentation of ear of 97.56%.

Sarangi, et al.,2017, [9] proposed a new method for automatic ear localization based on the modified Hausdorff distance (MHD). This method does not depend on pixel intensities and it was invariant to pose, shape, illumination, and occlusion in profile face images. Their presented method was evaluated on two datasets, the CVL face database [10] and the UND-E database [11], and achieved accuracy values of ear detection of 91% and 94.54%, respectively.

Kamboj, et al., 2019, [12] proposed a deep learning-based Ear Localization Model for Side Face Images, which was inspired by Faster-RCNN. Their model was tested on UBEAR-II and USTB-III Databases and achieved accuracy values of 95% and 99.08%, respectively.

The rest of this paper is organized in four sections; section 2 describes the proposed methodology, section 3 presents the details of experiment and results of the tests on all images of the database, and finally, section 4 presents the conclusions .

Proposed Methodology

In the suggested method, image preprocessing mechanisms are utilized for segmentation of ear from color images. The overall steps of the ear extraction method are shown in Figure-1.

Color Space Transformation

The HSV color space rearranges the geometry of RGB model in a cylindrical coordinate and takes the form of the cone. It is generally referred to as "hex cone model" [13], as in Figure-2. HSV color space contains three components: (i) H which indicates the hue component that determines the color, ii) S which indicates the saturation component, that specifies the purity of color, and (iii) V which indicates the value component, that determines the brightness or color intensity [14]. The conversions from RGB to HSV color models can be obtained by using the following equations [15]:

$$H = arccos \frac{\frac{1}{2}(2R-G-B)}{\sqrt{(R-G)^2-(R-B)(G-B)}} \quad (1)$$

$$S = \frac{max(R,G,B)-min(R,G,B)}{max(R,G,B)} \quad (2)$$

$$V = max(R,G,B) \quad (3)$$

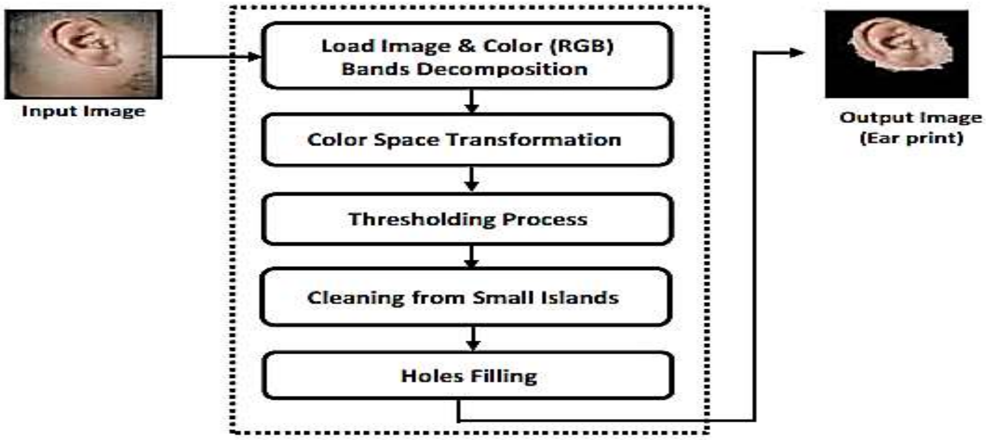


Figure 1- The layout of The Proposed Method

Figure-3 shows the hue, saturation, and value components after the conversion process from RGB to HSV color modal.

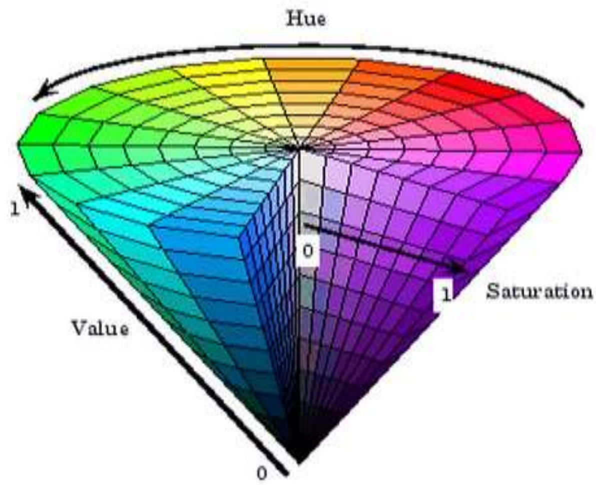


Figure 2- HSV color space representation

Thresholding Process

After the HSV conversion process, thresholding is applied to hue image for creating a binary image by using equation (4) [16]. At first, all pixel values in hue image are examined; if the value in hue image is between thr1 and thr2, this indicates a foreground region and takes a value of (1's); otherwise, it indicates the background region and takes a value of (0's). The result of this process is shown in Figure-4.

$$Bin(x,y) = \begin{cases} 1 & if\ Thr1 \leq h(x,y) \leq Thr2 \\ 0 & Otherwise \end{cases} \quad (4)$$

where Bin( ) is the produced binary image, h( ) is the hue image, and Thr1 & Thr2 are the thresholding values. In the proposed method, the best segmentation result is obtained when the threshold values are taken as 0 and 25 for Thr1 and Thr2, respectively.

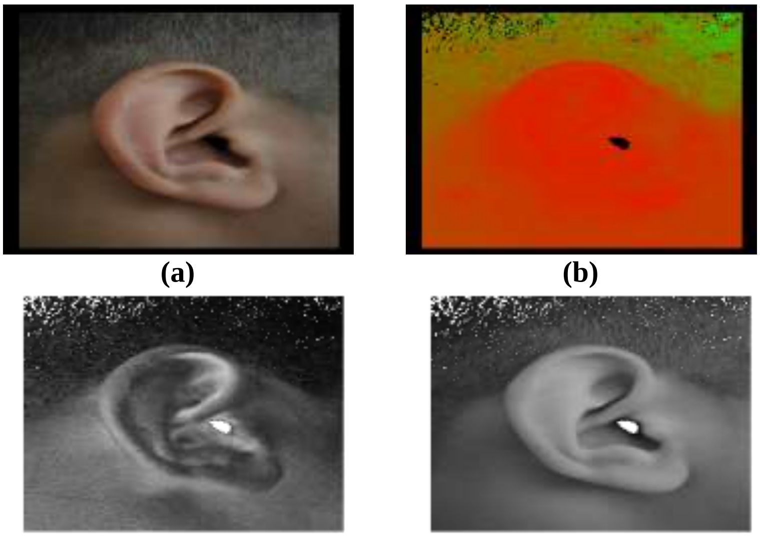
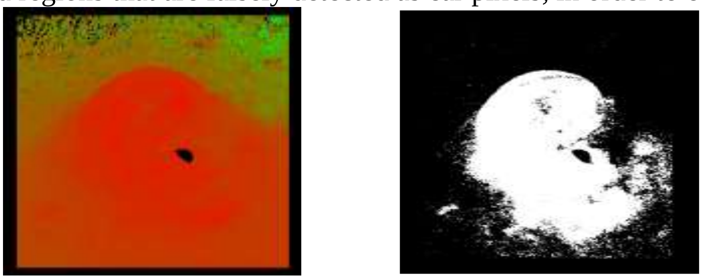


Figure 3- The three components of HSV color space; (a) input image, (b) Hue, (c) Saturation, and (d) Value .

2.3 Cleaning Small Islands

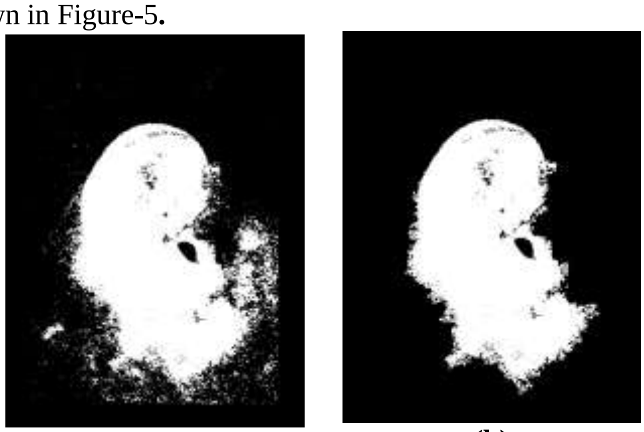
In this step, the seed filling algorithm that was previously described in detail [17-19]was used to remove the unwanted regions that are falsely detected as ear pixels, in order to obtain



(a) (b)

Figure 4- (a) Before thresholding, (b) After thresholding

a good segmentation performance. Thus, the pixel area in each linked region is measured to remove these islands. If the size of the linked region is greater than a predefined threshold (thr_size) then it is considered as an ear region, with a pixel value that is still equal to 1; otherwise it is considered as a non-ear region which will be removed and take a new value of to 0. The result after applying the seed filling algorithm is shown in Figure-5**.**



(a) (b)

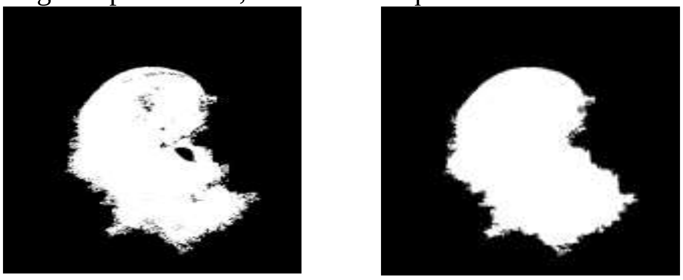
Figure 5- (a) before seed filling (b) after seed filling

2.4 Holes Filling

In this step, seed filling algorithm is used in order to fill the holes inside the ear region that are falsely detected as unwanted pixels. Therefore, this step is important for obtaining a good segmentation result. The result after the holes filling operation is shown in Figure- 6.

2.5 Allocating the Ear Area

This process involves the scanning of all pixel in the image resulting from the previous step (i.e., holes filling) and detecting the pixel value; if the value equals one then the new pixel value takes



(a) (b)

Figure 6- (a)before holes filling (b) after holes filling

the same value of the corresponding pixel from the original input image; otherwise, the value of a new pixel takes the 0's value (Figure-7).

(a) (b)

Figure 7- (a)before allocating ear (b) after allocating ear

Results and Discussion

The suggested method was tested on our own database of ear images which consists of 105 ear images taken from the right side of 105 subjects (6-70 years old). All the images were taken using three different models of Nikon camera (i.e., Nikon D3200, Nikon D5100, and Nikon D7200) under variant environments and illuminations. The resolution of the images from camera 1 was 690×1012, while that from camera 2 was 572×838 and from camera 3 was 690×1010 pixels, in jpeg format. The images were acquired over a period of 3 months. Figure-8 shows examples of ear images captured ins different environment and lighting conditions.

Figure 8- Samples of ear images from different subjects

To evaluate our proposed segmentation method, we used a performance metric (i.e., Detection Rate). Detection Rate is calculated by using equation 5 and it is defined as the number of correctly detected ears over the total number of ears in the database. Table-1 presents the results of the ear detection accuracy which corresponds to different ear images from three cameras.

$$Detection\ Rate = \frac{No.of\ correctly\ detected\ Ear}{Total\ No.of\ Ear\ Images} \times 100\% \qquad (5)$$

Table 1- Accuracy of the suggested ear segmentation method on the different datasets, with respect to numbers (#) and percentages (%) of correct detections.

Ear Images captured from 3 cameras (#images)	Correct detection (#)	Correct detection (%)
Captured from Camera 1 (18)	18	100%
Captured from Camera 2 (48)	46	95.83%
Captured from Camera 3 (39)	39	100%

The experimental results show that our method achieved a detection rate of 98.61% for ears segmentation in all tested images in the database. Hence, the proposed method uses fewer complexity steps for extracting ear region and is more accurate in comparison with the other methods described in the literature. For example, the method of Vélez, et al. [7] achieved an accuracy of detection rate of 78.33% which is less than the achieved detection rate of our proposed method.

In the thresholding process, the best threshold values in the isolation process that lead to best ear detection results were met when thresholding values were taken at Thr1=0 and Thr2 =25. Table-2 shows the results of the ear localization accuracy at different cases of Thr1 & Thr2 values.

Table 2- The impact of Thr1&Thr2 values on the results of the accuracy rate of the ear region localization.

Thr1	Thr2	Accurately Detected (#)	Poorly Detected (#)	Detection Rate (%)
5	16	58	47	55.23%
3	18	73	32	69.52%
1	18	79	26	75.23%
0	19	88	17	83.80%
2	22	99	6	94.42%
0	23	102	3	97.14%

Also, we used other segmentation performance metrics in order to evaluate the performance of our proposed method, which are Accuracy (AC), True Positive Rate (TPR), and False Positive Rate (FPR). These performance metrics are defined using the following equations [20]:

$$TPR = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \qquad (6)$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} \qquad (7)$$

$$AC = \frac{TP + TN}{TP + FP + TN + FN} \qquad (8)$$

where TP refers to the number of pixels that are correctly identified as ear points, TN refers to the number of pixels that are correctly identified as a background points, FP refers to the number of pixels that are identified incorrectly as ear points while they are actually background points, and FN refer to the number of pixels that are identified incorrectly as background points while they belong to ear points. Table-3 shows the results of our proposed method using the segmentation performance measures (i.e., TPR, FPR, and AC).

Table 3-Evaluation results using different segmentation performance metrics.

	TPR	FPR	Accuracy
Proposed method	0.95510	0.02385	0.966%

The proposed method gave an accuracy rate of 96.6% for segmentation of ears, while the value of FPR was 0.238, indicating that the proposed method is more accurate than the other methods described in the literature. For example, Prakash, et al. [5] and Sarangi, et al. [9] methods achieved accuracy values of ear segmentation of 94.6 % and 92.7 respectively, which are less than the accuracy of our proposed method.

Table-4 demonstrates some of the results from the proposed method, where ears of various shapes and sizes were precisely detected from different ear images. The results show that the proposed method is able to detect ear in the presence of little occlusion due to hair or glasses. The experimental results show that the proposed method is more efficient and less complex than the other previous segmentation methods which required more computational effort and failed in some cases to segment the ear accurately, especially for the ear images which are heavily occluded by the hair or poor quality.

Table 4- Shows Ear Segmentation Results from Different Images.

Input image	Output image
	
	
	
	
	
	
	

4. Conclusions

Ear image segmentation is a critical step of developing an automatic identification system based on ear biometrics. An efficient segmentation method is proposed in this paper, which is simple and accurate for the extraction of the ear region from color images. Firstly, the RGB color space is converted to an HSV color space. Then thresholding is applied for allocating the ear region. Lastly, to remove small islands and fill the gaps, the morphological operations were applied. The presented method was tested on many images which have different qualities. The experimental results showed that this method is efficient in segmenting ear images and achieved a high accuracy rate for the segmentation of the ear region. In the future, this proposed system can be used as a beneficial tool in the segmentation stage of the identification systems.

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