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Skin Detection using Improved ID3 Algorithm

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Abstract

Skin detection is classification the pixels of the image into two types of pixels skin and non-skin. Whereas, skin color affected by many issues like various races of people, various ages of people gender type. Some previous researchers attempted to solve these issues by applying a threshold that depends on certain ranges of skin colors. Despite, it is fast and simple implementation, it does not give a high detection for distinguishing all colors of the skin of people. In this paper suggests improved ID3 (Iterative Dichotomiser) to enhance the performance of skin detection. Three color spaces have been used a dataset of RGB obtained from machine learning repository, the University of California Irvine (UCI), RGB color space, HSV color space, and YCbCr color space. The experimental results demonstrate that the proposed system achieves accuracy up to 99.88%, 99.88%, and 99.80% in a dataset of RGB, a dataset of HSV, and a dataset of YCbCr respectively.

Keywords: Detection of Skin color, Machine learning, Decision Tree Algorithm, Improved ID3

اكتشاف الجلد باستخدام خوارزمية ID3 المحسنة

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الخلاصة

كشف الجلد هو تصنيف بكسلات الصورة الى نوعين من بكسلات هي جلدية وغير جلدية. في حين، لون الجلد يتأثر بالعديد من مشاكل مثل الناس من مختلف الاعراق و مختلف الاعمار ونوع الجنس. بعض الباحثين السابقين لقد حاولوا لحل هذه المشاكل من خلال تطبيق threshold التي تعتمد على فترات معينة للالوان الجلد. بالرغم، انها سريعة وبسيطة التنفيذ، انها لا تعطي اعلى كشف لتمييز كل الوان جلد الناس. في هذا البحث يقترح improved ID3 (Iterative Dichotomiser) لتحسين اداء كشف الجلد. تم استخدام ثلاث spaces color التي تعتمد على بيانات ال RGB التي تم الحصول عليها من مستودع تعلم الالي، جامعة كاليفورنيا Irvine (UCI)، RGB space color، HSV space color، و YCbCr color space. النتائج التجريبية توضح ان النظام المقترح يحقق دقة قد تصل الى 99.88%، 99.88%، و99.80% في كل من بيانات RGB، بياناتHSV ، و بيانات YCbCr على التوالي.

Introduction

The human skin color is created through a mixing of the blood red with melanin, which consists of two colors brown and yellow. The detection of skin aims to create rules used to detect skin pixels [1]. The detection of skin has an important role in both image processing applications and computer vision.

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It is applied in many fields like face detection, hand detection, personal identification, intelligent video surveillance, skin diseases, and human-computer interaction [2-3].

Whereas, the color of skin is sensitive to three issues that associated basically in changing the color of skin in that image like [1]:

1. Camera specification: The skin relied on the features of the sensor camera. Despite the image is taken under similar circumstances, it will vary from camera to another camera based on features of the camera sensor.
2. Race groups: People are classified into varying race groups like Asian, and African; these groups differ from one human to another human, in general of skin colors are range from white, yellow, and dark colors.
3. Individuals of the characteristics: Individuals of the characteristics like age and gender type, greatly contribute to change the color of skin.

In this research concentrated on solving the above three issues by using the improved ID3 algorithm, this proposed is used to detect skin pixels. The main aim of the proposed system is enhancing the performance of detection of skin color, skin detection dataset is used which picked through machine learning repository (UCI) [4].

Related Work

- In 2009 R.B. Bhatt et.al have presented a fuzzy decision tree method to detect skin pixels from the image based on skin segmentation dataset through randomly sampling color space RGB obtained from images of face of different ages of people like young, middle, and old, race groups of people like white, black, and Asian as well as gender type collected from FERET database as well as PAL database. The total of the learning is 51444 samples; however, the skin is 14654 samples and the non-skin 36790 samples. This method gives 94.10% accuracy in human skin color detection [5].
- In 2012 Al-mohair H.K. et al. have presented an artificial neural network and multilayer perception technique with a different number of neurons and hidden layers for detection of skin color in YCbCr color space with 420000 pixels and this technique is used for improving the distinguishing the skin pixels from non-skin pixels in various illumination conditions and it gives accuracy up to 83.3% in skin detection [6].
- In 2018 Bush.I.J. et al. have presented adaptive neuro-fuzzy inference system for determining skin pixels in the image through using two methods include neural network and fuzzy inference system was performed using the same of the dataset which belongs to this research. This technique presents a very high potentials for detecting human with two experiments based on a number of fuzzy rules. This results that obtained from the two experiments, the first experiment using 8 numbers of fuzzy rules gives 89.40% accuracy while the second experiment using 27 numbers of fuzzy rules gives 90.10% accuracy [7].

A dataset of the Skin Detection

In this research, a dataset of skin detection is utilized which was obtained from machine learning repository UCI [4]. It is obtained from skin textures of different images of face images of people of various ages, sex type like male and female, and race groups while non-skin pixels collected from arbitrary thousands of random sampling of textures. It consists of R, G, and B attributes (features), each value of each attribute represents integer value from 0 to 255 with two labels of the decision, 1 represents skin pixel and 2 represents the non-skin pixel. The total of the learning is 245057, a total of the skin of dataset is 50859 samples and a total of the non-skin of the dataset is 194198 samples, this dataset can be described in Table-1.

Table 1- Sample of skin detection dataset

R	G	B	Decision
122	84	73	1
112	163	164	2
. . .	. . .	. . .	. . .

HSV Dataset Description

HSV (hue, saturation, value); it separates illumination components from chrominance components. Consequently, Hue and saturation are combined with chrominance components and V is an intensity value that combined with brightness. A dataset of HSV extracts by transformation equation (1) on each integer value of each attribute of a dataset of RGB [8-9], a dataset of HSV as shown in Table -2.

$$\begin{cases} H = \arccos \frac{\frac{1}{2}(2R-G-B)}{\sqrt{(R-G)^2+(R-B)(G-B)}} \\ S = \frac{max(R,G,B)-min(R,G,B)}{max(R,G,B)} \\ V = max(R,G,B) \end{cases} \tag{1}$$

Table 2- Sample of skin detection dataset using HSV color space

H	S	V	Decision
0.037415	0.401639	122	1
0.503250	0.317073	164	2
. . .	. . .	. . .	. . .

YCbCr Dataset Description

YCbCr color is widely used in video information, European TV system, and compression application. It is a popular color space due to separate chrominance components from luminance components [8]. In this color space, (Y) represents luminance components and (Cb and Cr) represents chrominance components. Cb is the difference between the two components, the first component is a blue component, the second component is the reference value while Cr is the difference between two components, the first component is the red component, the second component is reference value [9]. The YCbCr dataset is extracted through applying the following matrix on each integer value of each attribute of a dataset of RGB [10], the dataset of YCbCr is shown as in Table-3.

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 0.279 & 0.504 & 0.098 \\ -0.148 & -0.291 & 0.439 \\ 0.439 & -0.368 & -0.071 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{2}$$

Table 3- Sample of skin detection dataset using YCbCr color space

Y	Cb	Cr	Decision
80.88491	-9.96191	17.97786	1
127.0527	8.500576	-21.9695	2
. . .	. . .	. . .	. . .

Data Preprocessing

In the real world, the dataset might contain noise, inconsistency, and missing values. Data preprocessing techniques are applied to the candid dataset in order to prepare, it for further analyzing the process. These techniques recreate the dataset into a new form which will be preferably known through the users and more efficacious for next processing [11].

Discretization

Discretization is one of the data preprocessing techniques which will convert continuous values to the range. It performs the recursive process on each attribute. The important part of the discretization process is choosing the better cut off points that segmentation the continuous values in the range [12-13].

In this research, convert each integer value from 0 to 255 of R, G, and B attributes into the range [0–19] as the following:

Table 4-RGB dataset after discretization technique

Bin	Range
0	[0-29]
1	[30-38]
2	[39-48]
3	[49-57]
4	[58-60]
5	[61-74]
6	[75-89]
7	[90-94]
8	[95-100]
9	[101-104]
10	[105-115]
11	[116-124]
12	[125-138]
13	[139-145]
14	[146-154]
15	[155-170]
16	[171-181]
17	[182-211]
18	[212-240]
19	[241-255]

Whereas, convert the values of H and S features from 0 to 1 into twenty bins by applying discretization can be described in Table-5 while the values of V attribute from 0 to 255 are converted into twenty bins as the following:

Table 5- HSV dataset after applying discretization technique

Bin	Range
0	[0-0.0999]
1	[0.1000-0.1899]
2	[0.1900-0.1999]
3	[0.2000-0.2499]
4	[0.2500-0.2699]
5	[0.2700-0.3499]
6	[0.3599-0.3699]
7	[0.3700-0.4499]
8	[0.4500-0.4699]
9	[0.4700-0.5499]
10	[0.5500-0.5699]
11	[0.5700-0.6499]
12	[0.6500-0.6899]
13	[0.6900-0.7499]
14	[0.7500-0.7699]
15	[0.7700-0.8499]
16	[0.8500-0.8699]
17	[0.8700-0.9499]
18	[0.9500-0.9699]
19	[0.9700-1]

Table 6-YCbCr dataset after applying discretization technique

Bin	Range
0	[0-0.0999]
1	[0.1000-0.1299]
2	[0.1300-0.1899]
3	[0.1900-0.2299]
4	[0.2300-0.2899]
5	[0.2900-0.3299]
6	[0.3300-0.3899]
7	[0.3900-0.4299]
8	[0.4300-0.4899]
9	[0.4900-0.5299]
10	[0.5300-0.5899]
11	[0.5900-0.6299]
12	[0.6300-0.6899]
13	[0.6900-0.7299]
14	[0.7300-0.7899]
15	[0.7900-0.8299]
16	[0.8300-0.8899]
17	[0.8900-0.9299]
18	[0.9300-0.9899]
19	[0.9900-1]

Normalization

Normalization defines a data preprocessing tool which used in the data mining system. Each attribute is normalized into little-specified range, like 0.0 to 1.0. It is useful for many classification algorithms like neural networks. There are many methods of normalization like min-max normalization, decimal scaling, and z-score normalization.

Min-max Normalization

Min-max normalization performs a linear transformation on the raw data [16]. It is computed by the following:

$$min - max \ = \frac{v(A) - min(A)}{max(A) - min(A)} (newmax - newmin) + newmin \quad (3)$$

Where: $v(A)$ represents the value of attribute A, $min(A)$ is minimum value of attribute A , $max(A)$ is maximum value of attribute A, $newmax$ represents 1, $newmin$ represents 0.

The YCbCr dataset is normalized into the range [0-1] by applying min-max normalization. Since, min-max normalization technique using a dataset of YCbCr gives a very low detection rate. Therefore, discretization that can be described in Table-6

The bins [0-19] are collected during many experiences depend on error and trail. These bins are utilized to obtain high detection of skin color.

Decision Tree Algorithm

In the late 1970s and early 1980s, J. Ross Quinlan advanced a decision tree algorithm named as ID3 (Iterative Dichotomiser). ID3 is one of the classification algorithms. The fundamental of ID3 algorithm based on selecting attributes utilized information gain as feature chosen criterion, choosing a feature with the largest information gain to create nodes and constructing branches of the decision tree by the various values of the node building the decision tree and branches recursively until a specific subset of the tuples belongs to the same the decision [11].

The information gain can be calculated through the following steps: -

1. Entropy: The entropy (Ent) computes the amount of information on each attribute.
   Now, to compute entropy (Ent) for each attribute using two equation:

a. Compute the mount information needed to classify in the instance (S):

$$Ent(S) = -\sum_{i=1}^{m} P_i \log(P_i) \quad (4)$$

Where:
S is a training set, that will be segmented into sets $\{S_1, S_2, \dots, S_v\}$,
P_i is representing the proportion of S belonging to decision D and can be computed by the following equation:

$$P_i = \frac{|D_i, S|}{|S|} \quad (5)$$

Where:
D_i, S is an arbitrary instance in S belongs to a decision.
c. Compute the mount information for each attribute A in training set S to depend on the segmenting by A.

$$Ent_A(S) = \sum_j^v \frac{|S_j|}{|S|} \times Ent(S_j) \quad (6)$$

Where:
S_j: a subset of S $\{S_1, S_2, \dots, S_j\}$,
A: is an attribute.
2. Information gain: the feature A that has the largest information gain is used as the segmenting feature at a leaf node. Information gain of training set S on attribute A is computed by:

$$Gain(A) = Ent(S) - Ent_A(S) \quad (7)$$

Improved ID3 Algorithm

The ID3 algorithm is used with the RGB, HSV, or YCbCr datasets after applying equal frequency discretization. It can be seen many rules don’t have the label of the decision when attributes are a segment and an additional feature is not found in the dataset, there is a need for next segmenting to distinguish the skin from non-skin pixels. Therefore, the ID3 algorithm can improve by counting the number of the label of the decision for the final attribute, if a number of skin pixels are larger than non-skin pixels then the pixel represents skin, otherwise, the pixel represents non-skin.

Detection of Skin color

Figure-1 demonstrates the improved ID3 algorithm for human skin color detection, which composed of RGB, HSV, and YCbCr color spaces. This algorithm is used to classify the pixels of the image into the skin pixels and non-skin pixels. The output is a new image in which only skin pixels are considered as red color pixels while, non-skin pixels are returned. Three color spaces are applied using the improved ID3 algorithm as the following:

1. RGB Color Space: In the first, the discretization technique is applied on a dataset of RGB, in order to decrease the amount of the time complexity of detection. Apply improved ID3 on a training dataset of RGB then assess the improved ID3 by using the new RGB image as input, the discretization applies on the pixels of the RGB image then, these pixels of the RGB image match with a set of rules. Finally, the skin pixels of the RGB image are detected.
2. HSV Color Space: In the first, obtain HSV color space from a dataset of RGB through using equation (1), the discretization technique is also applied to a dataset of HSV. In order to decrease the amount of the time complexity of detection. Apply improved ID3 on a training dataset of HSV then assess the improved ID3 by using a new the RGB image as input then, this image is transformed into HSV image using equation (1), the discretization applies on the pixels of HSV image then, these pixels of HSV image matches with a set of rules. Finally, the skin pixels of this image are detected.
3. YCbCr Color Space: In the first, obtain YCbCr color space from a dataset of the RGB applying equation (2). After that, this color space is normalized to the range [0–1] by using min-max normalization technique as shown in equation (2), then the discretization technique is also applied to a dataset of YCbCr. Apply improved ID3 on a training dataset of YCbCr then assess the improved ID3 by using the new RGB image as input then, this image is transformed into YCbCr image, the discretization and normalization techniques apply on pixels of the image then, these pixels of the image match with a set of rules. Finally, the skin pixels of this image are detected.

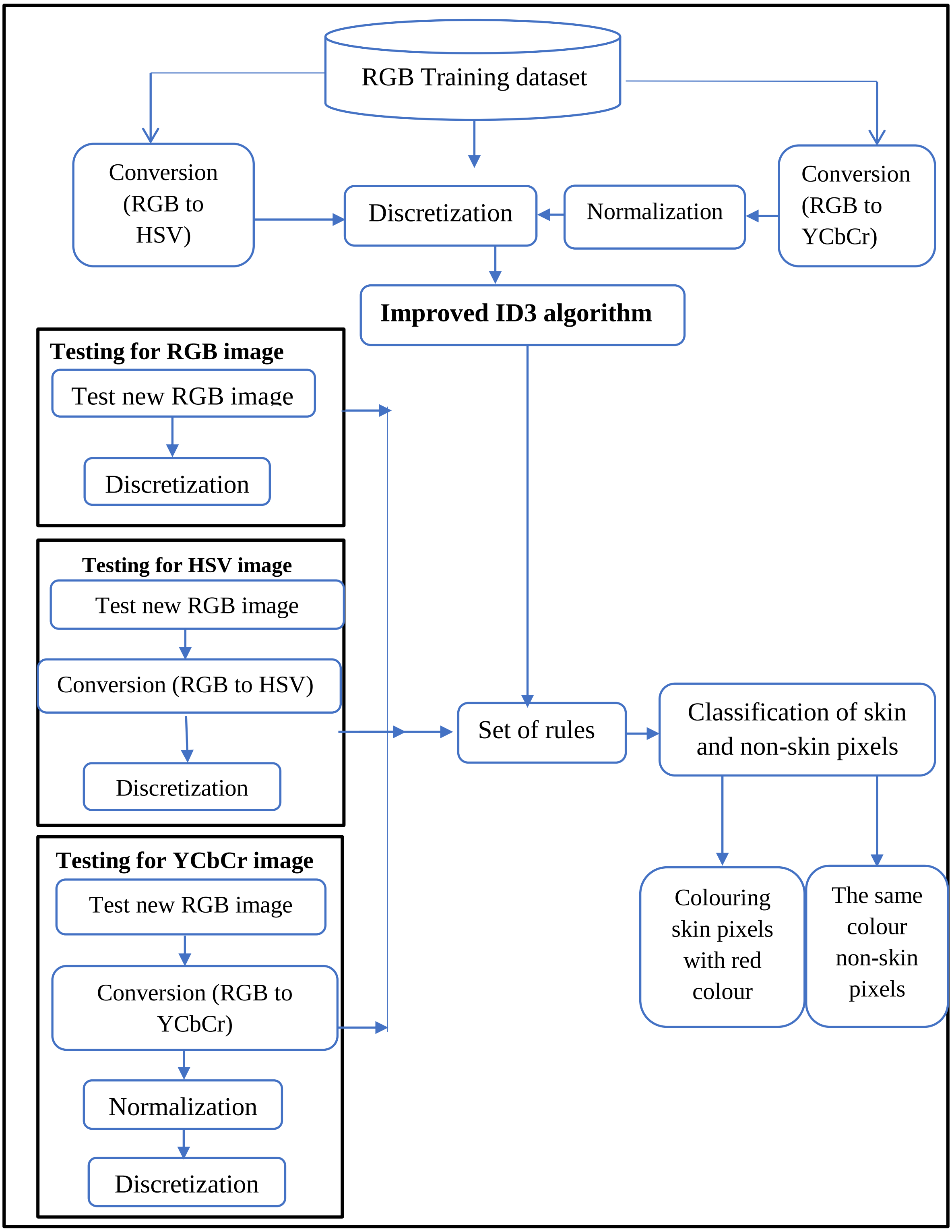

Figure 1- Improved ID3 of human skin color detection

Experimental Results

The experimental results are not especially devoted to a specific color space. Where implementing a proposed system for skin detection was conducted using three experiences RGB, HSV, and YCbCr color spaces. The samples were selected from different sources on the internet, images consist of different races groups, various ages, and changing illumination conditions. The results obtained after applying improved ID3.

Figure 2- Results of RGB image for skin detection using the improved ID3 algorithm

Figure 3- Results of RGB image for skin detection using improved ID3 with decreasing Illumination

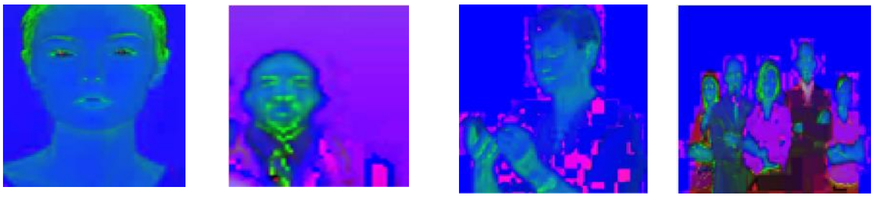

Figure 4- Results of HSV image for skin detection using the improved ID3 algorithm

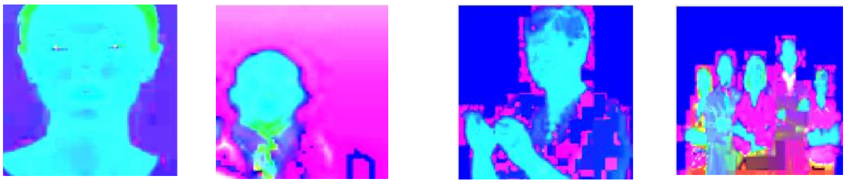

Figure 5- Results of HSV image for skin detection using the improved ID3 algorithm with decreasing illumination

Figure 6- Results of YCbCr image for skin detection using improved rules of ID3

From Figures-(2-6), show the results of skin detection for experiences 1, 2 and 3. This indicates that high detection on the image was found with experiment 2 after decreasing the illumination of the image to 0.3. Whereas, the performance of improved ID3 assessed through segmenting dataset into two parts are training and testing sets. In this research, the training set is 80% and the testing set is 20% as the following:

Table 7- Measure performance for improved ID3

Algorithm	Accuracy	Error Rate	MAE	RMSE
Improved ID3 in RGB dataset	99.88%	0.12%	0.0010	0.0223
Improved ID3 in HSV dataset	99.88%	0.12%	0.0012	0.0353
Improved ID3 in YCbCr dataset	99.80%	0.02%	0.0020	0.0443

In Table-7 when using improved ID3 through experiences 1 and 3 achieve high accuracy, whereas, the RGB and YCbCr color space don't produce better detection rate on the images, where these images have been collected from various sources of the web, not from the testing set of the dataset. This research implements using the MATLAB R2015b program. Table-8 demonstrates the performance of the proposed system was compared to previous authors using the same dataset.

Table 8- Performance of other methods and the proposed system

Machine learning techniques	Total of datasets	Accuracy
Adaptive neuro-fuzzy inference systems	245057 pixels	(89.40% - 90.10%)
Improved ID3 in HSV dataset with decreasing illumination	245057 pixels	99.88%

Conclusion

In this research, skin detection using improved ID3 with three experiences. Firstly, RGB color space is extracted from machine learning repository (UCI). Secondly, HSV color space is extracted from RGB dataset. Finally, YCbCr color space is extracted from RGB. However, Improved ID3 provides accuracy of 99.88%, 99.88%, and 99.80% in RGB, HSV, and YCbCr datasets respectively. The improved ID3 algorithm achieves high detection using HSV dataset with decreasing illumination. The proposed system has the ability to adapt to the race groups of people, different ages of people and gender type.

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