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Research Article

A Skin Detection Approach Based on Color Distance Map

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We propose a reliable approach to detect skin regions that can be used in various human-related image processing applications. We use a color distance map, which itself is a grayscale image making the process simple, but still containing color information. Based on this map, we generate some skin as well as nonskin seed pixels, and then grow them to capture the appropriate regions. This approach outperforms the existing approaches in terms of segmenting solid and perfect skin regions. It does not generate much noisy segments. Moreover, it does not need any prior training session and can adapt to detect skin regions from images taken at different imaging conditions.

1. INTRODUCTION

Skin segmentation is a major component in human-computer interaction- (HCI-) based applications such as gesture analysis, facial expression detection, face tracking, human motion tracking, and other human-related image processing applications in computer vision and multimedia such as filtering of web contents, retrieving in multimedia databases, video surveillance, videophone, and videoconferencing applications.

The main target of skin detection is to detect skin pixels in images and thereby generate some skin regions. These regions are then further investigated according to the focus of the specific application. A successful recognition of skin regions eases subsequent parts of a system those do the detail processing of such regions. If candidate regions are erroneously detected, then a good amount of effort by the application will be used in unsuccessful diagnosis. Further, if the detection process misses any skin region or provides regions having lots of holes in it, then the reliability of applications will also decrease. Hence, this initial step should be made sufficiently reliable to maintain the efficiency of the systems those depend on it.

Many different skin detection approaches have been proposed in the literature over the past few years. However, the performance of most of the approaches is satisfactory for a limited set of real world conditions and skin types only [1]. Early approaches of skin segmentation deal with grayscale images. However, these approaches suffer from inappropriate detections as well as the rejections of skin pixels since grayscale images lack the appropriate variation in color.

Recently, skin detection methodologies based on color information have gained much attention since skin color provides computationally effective and robust information against rotations, scaling, and partial occlusions [1]. Hence, color may serve as a very effective tool for identifying skin areas if the skin color pixels can be represented, modeled, and classified accurately. However, real world skin detection can be a challenging task, as the skin appearance in images is affected by various factors. For example, different illumination levels like indoor, outdoor, highlights, shadows, and so forth. may cause change in skin color (color consistency problem [1]). Skin color of the same person in same illumination condition may differ in different images taken by cameras having different characteristics like spectral reflectance, sensor sensitivities, and so forth. Skin color also differs for different persons coming from different ethnic groups [2]. Some individual characteristics such as age, sex, and body parts also affect the appearance of skin color [1]. Some other reasons may also make changes in skin color such as subject appearances (makeup, hairstyle, and glasses), background colors, and motions. Efforts have been given to minimize the effect of these factors, especially to normalize the color, so that the image is less sensitive to the illumination. Several approaches are proposed to make use of color space transformation [3–6] or ratios of different color channels [7, 8]. However, most of the transformed spaces that deal with chrominance and some color information are also lost in the process of separating luminance from chrominance.

We may categorize the existing methods for classifying skin and nonskin pixels into three broad categories: parametric, nonparametric, and explicit threshold-based skin cluster classifiers [1, 9]. In *parametric* methods, single/Gaussian mixture models [1] are used to model the skin color distribution in different color spaces. For example, in [10], skin color distribution is modeled by an elliptical Gaussian joint probability density function. Mixture of Gaussian (MoG) [11] models is composed as sum of some Gaussian kernels. However, the classification speed of MoG is very slow as it evaluates each of these kernels for every pixel. It is very slow in training phase as well [12]. Moreover, it also suffers from inaccuracy as it has to depend on the approximated parameters instead of the actual distribution of skin colors. *Nonparametric* methods estimate skin color distribution from the histogram of the training data [12]. Such methods estimate a statistical model of the distribution of skin color by training the algorithm with a number of training data. However, an accurate statistical model requires, theoretically, infinite number of training data. Hence, a perfect statistical model is yet to be achieved. The models may have a number of holes and erroneously low contributing colors in it, which may lead to incorrect or fragmented segments and thus makes it applicable in a limited range of imaging conditions. *Explicit threshold-based skin cluster classifiers* are the simplest and often applied methods [1, 9] to classify skin and nonskin pixels. These methods explicitly define the boundaries of the skin cluster in certain color spaces [5, 9, 13–19]. They propose a set of fixed skin thresholds specifying some heuristic rules in a given color space. The key idea behind such approaches is that skin pixels' coordinates will have similar values in appropriately chosen color space. Such methods can be used right away without requiring any training phase. However, they may lack the flexibility to work under different imaging conditions, since these approaches are guided by some rigid values. This may result in inaccurate classification of pixels. To make the explicit skin cluster classifiers flexible, a genetic algorithm-based technique is proposed in [9]. However, it may not adapt with different images, since its thresholds are determined by a specific set of training pixels.

Basically, the main aim of skin segmentation is to find skin regions in images rather than skin pixels only. However, most of the existing methods are pixel-based classifiers that rely only on pixel information. Hence, most of them may provide with noisy pixels and incomplete or partial segments.

In this paper, we present an adaptive skin segmentation algorithm to extract skin areas in images to be used in human-related image processing applications. We make use of a standard skin color (SSC) for generating a color distance map (DM). The DM itself is a grayscale image making the procedure simple enough while it still contains the color information too. Moreover, the DM can reliably be generated without much prior knowledge about current image.

The proposed method basically uses an explicit threshold-based skin cluster classifier and provides enhanced performance in varying imaging conditions. This improvement in performance is achieved by adaptively selecting the SSC-based on the test image, which avoids the use of fixed thresholds. Moreover, the proposed approach uses region information to generate solid skin regions, so that the segmented result is free from noisy/scattered pixels and fragmented segments.

The rest of the paper is organized as follows. Section 2 presents the proposed approach in detail, performance analysis of this approach is presented in Section 3, and Section 4 concludes the paper.

2. THE PROPOSED METHOD

We propose an explicit skin cluster classifier-based segmentation method, which can successfully handle some variations in imaging conditions. Generally, it is well accepted that there is no single color system, which is suitable for all sorts of color images [6]. Therefore, it is unnecessary to insist on the adoption of a specific color system in the skin classification algorithm [17]. Hence, we do not strictly mention any specific color space here (we use RGB space as an example only). Our focus is mostly on the skin and nonskin pixel classification techniques, rather than on color space itself. Moreover, the proposed method is applicable in any color space using any existing explicit skin cluster classifier in that color space.

Defining skin clusters in color spaces and handling vector (color) images, especially in different imaging conditions, are complicated procedures. On the other hand, handling scalar (grayscale) images is much simpler, but it faces lack of color information to perform the job acceptably. Hence, we propose a color distance map (DM) [20] which itself is a grayscale image, but contains the color information. Moreover, the proposed approach mainly uses this DM, keeping the procedure simple and informative enough. The procedure is simple because it handles grayscale values only and informative because it implicitly makes use of color information in the disguise of grayscale image while retaining shape information that can confidently identify the skin segments.

Before presenting the proposed skin segmentation method, we define some important terms that will help to describe the method in detail.

Definition 1 (standard skin color (SSC)). The standard skin color (SSC) is a color in a color space that certainly represents skin. Usually, it represents the center point of skin cluster in a certain color space. It is denoted as a vector $(C_{1s}, C_{2s}, \ldots, C_{ns})$, where C_i denotes the color coordinate and n is the dimensionality used to specify skin cluster in a color

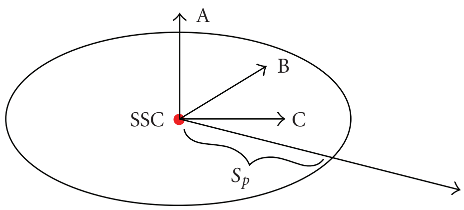


Figure 1: Effect of difference in spread in calculating color distance (CD).

space. For example, the SSC in RGB color space may be denoted as (R_s, G_s, B_s).

If a certain explicit threshold-based classifier defines a skin cluster using ranges of color coordinates $[C1_{\text{start}}, C1_{\text{end}}], [C2_{\text{start}}, C2_{\text{end}}], \ldots, [Cn_{\text{start}}, Cn_{\text{end}}]$, then the corresponding SSC will be defined as $((C1_{\text{start}} + C1_{\text{end}})/2, (C2_{\text{start}} + C2_{\text{end}})/2, \ldots, (Cn_{\text{start}} + Cn_{\text{end}})/2)$. If skin cluster is approximated by Gaussian distribution, then the mean of the distribution may serve as SSC.

Definition 2 (color distance (CD)). We define color distance (CD) as the Euclidean distance between a certain color and SSC, scaled by the spread, *Sp*, of skin cluster in the direction of that color from the SSC. Mathematically, CD of the color $(C_1, C_2, \ldots, C_n)$ is $\sqrt{\sum_{i=1}^{i=n}(C_i - C_{i_s})^2} / Sp_{(C_1,C_2,\ldots,C_n)}$. For example, CD of color (R, G, B) is $\sqrt{(R - R_S)^2 + (G - G_S)^2 + (B - B_S)^2} / Sp_{(R,G,B)}$. CD represents how distant a color is from the SSC. It is related to the potential of a color to be considered as skin. The lower the CD is, the higher the chance is.

Assume that the ellipse in Figure 1 represents a skin cluster in a color space. Three color points (A, B, and C) are shown that are geometrically equidistant from the SSC. However, it is clearly perceivable that these three colors do not have the same likelihood to be taken as skin. This is because of the nonuniform spread of color coordinates in the skin cluster. The lower the spread is, the higher the rate of decrease in skin likelihood is. The Euclidean distance cannot take this spread into account. We scale the Euclidean distance down by using the spread, *Sp*, of the cluster in the particular direction to which the Euclidean distance is calculated. The Euclidean distance is less scaled in the direction where the spread is small, than that in the direction of larger spread of skin cluster. Hence, the use of *Sp* works well as a normalization factor.

Definition 3 (color distance map (DM)). Color distance map (DM) [20] is a grayscale image generated from a color image by setting CDs of pixel colors at corresponding position and linearly transforming them to grayscale range, that is, [0, 255] according to 1:

$$\text{DM}(x, y) = \frac{d(x, y) - \min_{\forall x,y}(d(x, y))}{\max_{\forall x,y}(d(x, y)) - \min_{\forall x,y}(d(x, y))} \times 255, \quad (1)$$

where, $d(x, y)$ denotes the CD of the color of the pixel located at coordinate (x, y) of the image.

In some cases, however, generation of DM may not be such straightforward, when

(i) a classifier defines more than one skin cluster in certain color space, that is, there will be more than one SSC as well;

(ii) the decision making criteria of threshold-based classifier include some constraints (conditional operators) rather than specifying a range of color values only.

To handle the first problem, we define one SSC for each skin cluster and create an initial DM for each of them. Then, the final DM is generated by taking the smallest CDs at corresponding positions among initial DMs ((4) provides one such example). In other words, the final CD of a pixel is the minimum of its CDs in the initial DMs. Hence, the selected CD corresponds to the closest skin cluster of that pixel color. Thus, a single DM ensures to represent all the skin clusters specified by the classifier.

The second problem can easily be handled by setting a maximum possible CD for the pixel colors failing to satisfy the conditions/constraints.

Here, we present one simple and classical RGB color space-based classifier described in [9, 14] as an example. It takes two different conditions (involving strict thresholds) into account: uniform daylight and flash or lateral illumination, as presented in sets of equations in (2) and (3).

Uniform daylight illumination:

$$\begin{gathered} R > 95, \qquad G > 40, \qquad B > 20, \\ \text{Max}\{R, G, B\} - \text{Min}\{R, G, B\} > 15, \\ |R - G| > 15, \quad R > G, \ R > B. \end{gathered} \quad (2)$$

Flashlight or daylight lateral illumination:

$$\begin{gathered} R > 220, \qquad G > 210, \qquad B > 170, \\ |R - G| \leq 15, \quad B < R, \ B > G. \end{gathered} \quad (3)$$

This classifier classifies a pixel as skin only if either of these two set of conditions is true. Throughout this paper, we refer to this method as "traditional RGB-based method/algorithm."

At first, SSC is set as the middle of the skin cluster specified by inequalities in the first line of (2), that is, $(R_s, G_s, B_s) = (175, 147.5, 137.5)$. Then, an initial distance map is generated based on CDs. The corresponding values of the pixels, which fail to satisfy the inequalities in the second and the third lines of (2), are then set to 255. Thus, we get a grayscale image, Map_1, according to (2). Using the same strategy, we generate another grayscale image, Map_2, following (3). Then, we combine them into a single DM, denoted as M, according to (4):

$$M(x, y) = \text{Min}\{\text{Map}_1(x, y), \text{Map}_2(x, y)\}, \quad (4)$$

where, (x, y) represents pixel coordinate in the image.

Equations (2) and (3) define two skin clusters in RGB color space. By considering the lower CDs between these two, (4) assures to represent the distance to the closer cluster. Moreover, because of scaling the Euclidean distance by Sp, the CDs are also normalized according to the spread (size) of the skin clusters. For the skin color cluster having small distribution, the distance to the SSC is given more weight than the distance to other SSC with large distribution. Hence, the DM is consistent with both sets of conditions given in (2) and (3).

Here, we mention some properties of DM.

Property 1. DM represents skin likelihood of pixel colors regardless of the number of skin clusters specified by the classifier.

DM values represent the prospect of each pixel to be taken as a skin (as well as a nonskin) pixel. The lower the value is, the higher (lower for nonskin ones) the possibility is. This property enables a single DM to represent the skin likelihood of a pixel, even if the original classifier defines several skin clusters in color space (since the smallest of all CDs of one pixel in the initial DMs is considered, it represents the prospective skin cluster that the corresponding color may fall into).

Property 2. DM contains color and shape information.

Though DM itself is a grayscale image, it still can provide color information with respect to SSC. Hence, processing a DM is relevant to processing in color spaces.

Since CDs represent actual distance in the color space, DM retains most shape information (e.g., amount of changes in color of the neighboring pixels) that is present in the image.

Property 3. The distribution of CDs of skin pixels in any image is approximately Gaussian (more specifically, right half of Gaussian since we take absolute values in calculating the CDs).

Experimental proof

To investigate the correctness of Property 3, we used Compaq skin and nonskin databases [12, 21] and IBTD face database [22]. These databases provide skin masks along with the original images. We randomly selected 300 and 200 skin masks from the Compaq skin and nonskin database and IBTD face database, respectively. We also took some images from the GTAV face database [23] and the Internet, and then manually segmented skin regions in those images. We produced DM for these skin regions and generated histogram of DM. We then tested statistically, using the well-known Jarque-Bera test [24–26], whether the distribution of the CDs falling at the right side of SSC is half of Gaussian. Skin regions of all test images were found to pass the test.

We also calculated the standard deviation, σ, of the portion of histogram at the right side of SSC. We then generated ideal data for a Gaussian distribution having the mean at SSC and standard deviationσ and plotted these values along with the histogram values of the DM. The two series were found visually much closer for all test images (Figure 2 presents two such graphs). We also counted the summation of difference between corresponding values of these series and found that it is less than 20% of total pixels for every image. It also advocates in favor of considering the distribution of CDs of skin pixels in an image as Gaussian.

Our method requires selection of a suitable color space and an explicit skin cluster classifier in that color space. It searches for a standard skin color, which is the most considerable to be at the center of the distribution of skin pixels in the input image under processing. It then generates a color distance map based on which some portion of skin regions as well as nonskin regions are generated. These regions are then grown based on their neighborhood information, which make the segments solid to get rid of noisy and fragmented segments. Figure 3 presents an outline of the proposed approach for skin detection. The complete approach is described in the following subsections.

2.1. Selecting standard skin color (SSC) adaptively and generating the DM

To handle various situations, we propose an adaptive technique to select SSC based on test image. As mentioned earlier, the grayscale values in DM of skin regions of an image have right half of a Gaussian distribution. Hence, if the SSC can be perfectly chosen, we can have DM having the distribution of CDs fitted with the right half of an approximately zero-mean Gaussian distribution. For variation in skin color due to different imaging factors, however, skin cluster varies from image to image. Hence, in real world conditions, we might not have a distribution like the right half of a zero-mean Gaussian distribution. In such cases, it will fit with right half of a μ-mean (say) Gaussian, which means we may expect the SSC to be somewhere very close to the colors having CD μ. Hence, we redefine the SSC with the average of pixel colors having CD μ and regenerate the DM. This new SSC will shift μ to a lower value. Iterating this process, we will eventually find a μ close enough to zero.

Property 1 of DM mentions that the CDs of skin pixels are very small compared to the nonskin ones. Combining Property 1 and Property 3 of DM, we find that if some skin regions exist in the image, a right half of Gaussian distribution is likely to exist in smaller gray levels in histogram of DM. To search for such distribution, we first look for the first significant maxima (possibly the mean, μ) in the histogram and first significant minima (possibly the end of the distribution, Th) after μ. If the histogram components in the range $[\mu, Th]$ successfully pass a test of Gaussianity, then we consider it to represent skin regions. Otherwise, we consider that there is no skin region in the image.

We start by generating an initial SSC and DM as mentioned in Definition 1. Then, we refine the SSC (as well as the DM) according to Algorithm 1. In step 3 of this algorithm, we use the Jarque-Bera test [24–26] of Gaussianity.

This procedure supports handling images with distorted skin color. In such cases, the skin cluster generally shifts from its original position defined by skin cluster classifiers. Hence,

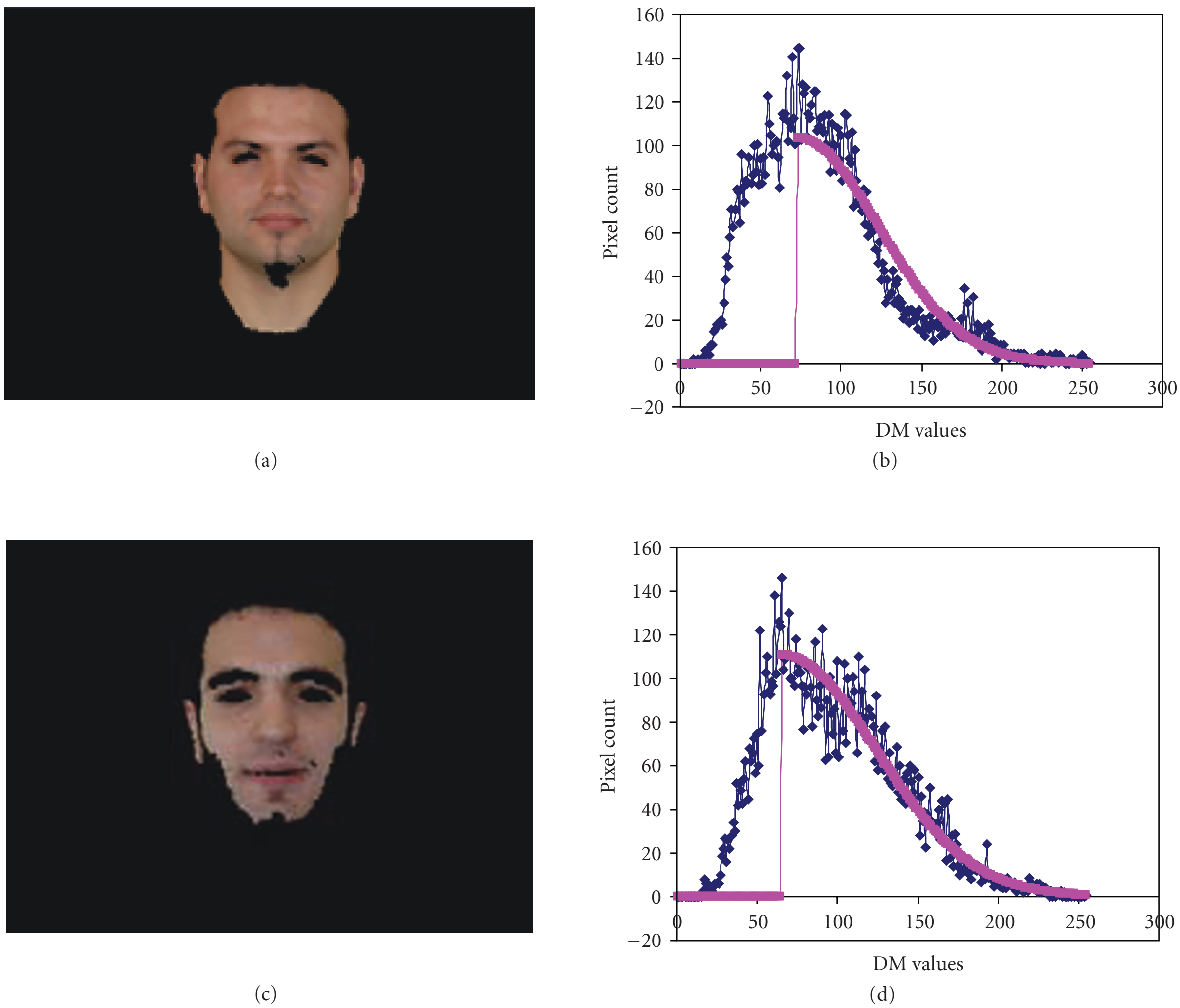


Figure 2: Distribution of skin pixels. Left column shows hand-segmented skin regions, and the right column shows the histogram of corresponding DM along with ideal Gaussian curves (smooth one).

the traditional classifiers may not classify it correctly. On the other hand, the proposed method can bend itself toward such changes in skin color. The selection of μ and Th is data driven and flexible for different images. By selecting a different SSC, it moves into the skin cluster of the image in use, and all the three properties of DM hold for the image.

In most of the images, step 1 to step 10 (in Algorithm 1) need to iterate 3 or 4 times only, which add a considerable overhead to the system. This advocates for the feasibility of the abovementioned SSC selection procedure to be used in real world applications. This selection procedure, however, works well under two assumptions:

(i) *skin region in the image is significant*. It assures that if a lower significant minimum is selected, then also it will cover some portion of skin area;

(ii) *different skin region in the image is similarly illuminated*. This assumption ensures that it will include some skin pixels from all/most of the skin regions in the image.

To make this approach more flexible to handling variations in such assumptions needs further investigation. We leave it as our future work.

2.2. Looking for seed regions

The purpose of this step is to select some pixels that undoubtedly come from skin regions and some other pixels that certainly do not represent skin. The straightforward way (in ideal cases) for the former one is to select the pixels having SSC. However, it will not work in most of the real images for the illumination and other natural variations. In such cases, a better way is to take pixels that are pretty much closer to the SSC. We take two thresholds, T_L and T_H, which represent the first and the last significant local minima of the histogram of DM, respectively. Here, these two thresholds are not rigid as well (the local minima may vary for different images). We then generate the seeds for skin and nonskin regions using algorithm in Algorithm 2. The rest of the pixels are treated as undefined pixels to be determined in the later step.

Algorithm Find_SSC()

Input Parameter
H: The histogram of DM
ε: A threshold specifying satisfactory value of μ

Output parameter
C: The refined SSC for this image

Procedure
1. **Set** μ = first significant local maximum in *H*.
2. **Set** *Th* = first significant local minimum in *H,* where $Th > \mu$.
3. **If** components of *H* in $[\mu, Th]$is close to right half of Gaussian **then**
4.   **If** $\mu < \varepsilon$ **then**
5.   Return *C*.
6.   **Else**
7.   *Set* C = Median of color of pixels whose CD is μ
8.   Generate a new DM, *M*, with respect to C as SSC
9.   Generate *H* of *M*
10.   Go to step 1.
11.   **End If**
12. **Else**
13.   *H* does not represent any skin region
14. **End If**

Algorithm 1: Algorithm to refine SSC.

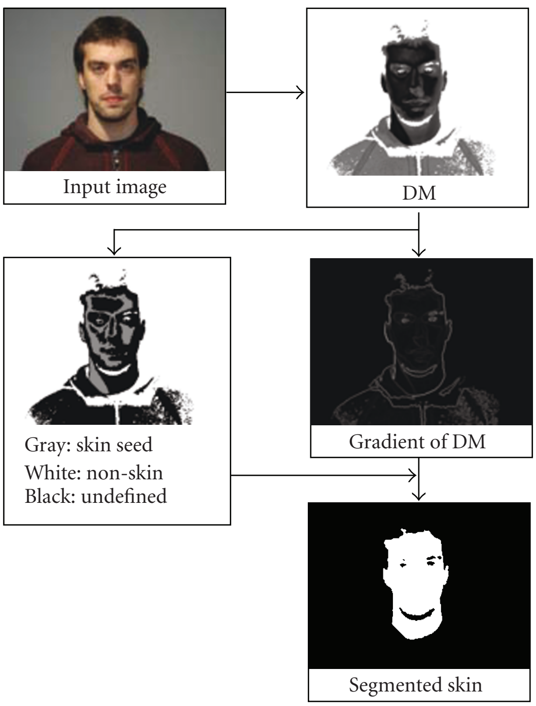


Figure 3: Pictorial view of the proposed approach.

Algorithm Find_Seed()
Input Parameters
    M: The refined DM of the test image.
    T_L: A low threshold.
    T_H: A high threshold.
Procedure
1. **If** $M(i, j) \leq T_L$ **then**
2.   The pixel at position (i, j) is a skin pixel.
3. **Else If** $M(i, j) \geq T_H$ **then**
4.   The pixel at position (i, j) is a non-skin pixel.
5. **Else**
6.   The pixel at position (i, j) is an undefined pixel.
7. **End If**

Algorithm 2: Algorithm for determination of skin and nonskin seeds from the distance map.

2.3. Region growing

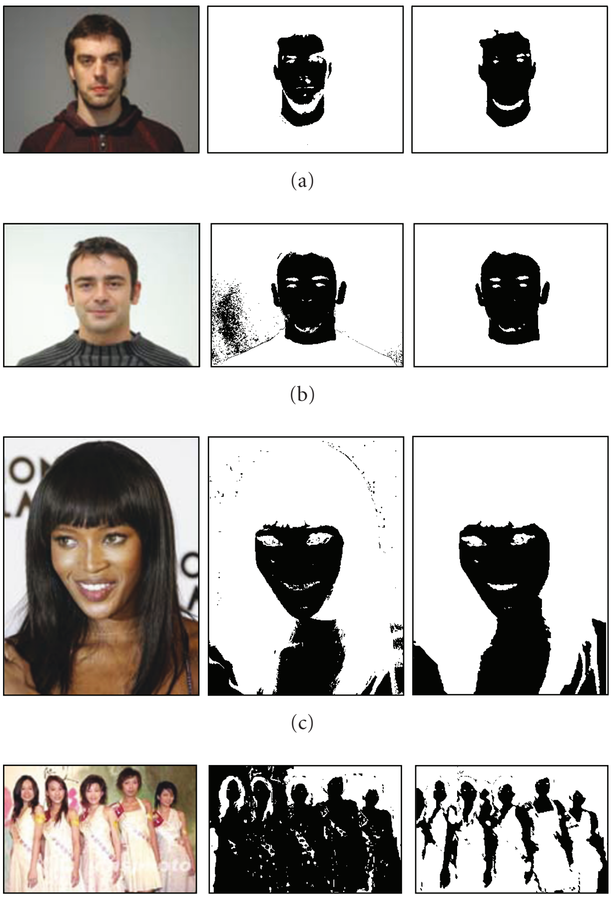
We use region information to process the undefined pixels. We take the gradient magnitude of the color distance map *M* and then apply the marker-based segmentation algorithm [27] to grow both skin and nonskin regions. The algorithm proceeds by processing the undefined pixels in the neighborhood of already labeled regions. At each step, it selects the pixel having the lowest gradient magnitude among these pixels. If the neighborhoods of this pixel come from different regions, it is labeled as a boundary pixel of these regions. Otherwise, it is labeled as the same region as its neighborhood.

To minimize the searching for minimum gradient magnitude, the region growing uses an ordered queue—a list of *n* queues, where *n* is the number of available levels in the

Algorithm Region_Growing
Input Parameters
G: Gradient magnitude of DM
S: Skin seed points
NS: Non-skin seed points
Output Parameters
Seg: Segmented image of the size same as G.

(i) Label each pixel in Seg as "skin", "non-skin" or "undefined" according to S and NS.
(ii) Add the neighboring pixels of labeled region in the respective queues according to their gradient magnitude levels.
(iii) While *all queues are not empty* do
 a. Pick a pixel p from the first available nonempty queue of the ordered queue according to priority of queues.
 b. If p has similarly labeled neighbors, then it is labeled as them. Otherwise, it is labeled as a boundary pixel.
 c. For each undefined neighboring pixel q of p
  i. If q is not already added in queue, add q in the respective queue according to its gradient magnitude level.

Algorithm 3: Algorithm for region growing.



(a)

(b)

(c)

(d)

Figure 4: A few images showing the results of applying the traditional RGB-based method and the proposed method. In each set, the first, the second, and the third images represents input image, image after segmenting using traditional RGB-based method, and the proposed method, respectively.

gradient image. The queue dedicated to store zero levels gets the highest priority, while the queue for level $n-1$ gets the lowest. The procedure proceeds as described in Algorithm 2.

Here, the region growing algorithm implicitly makes use of homogeneity and edge information by processing pixels in the ascending order of the gradient magnitude.

The segmented regions grown from the skin seeds are then considered as skin regions.

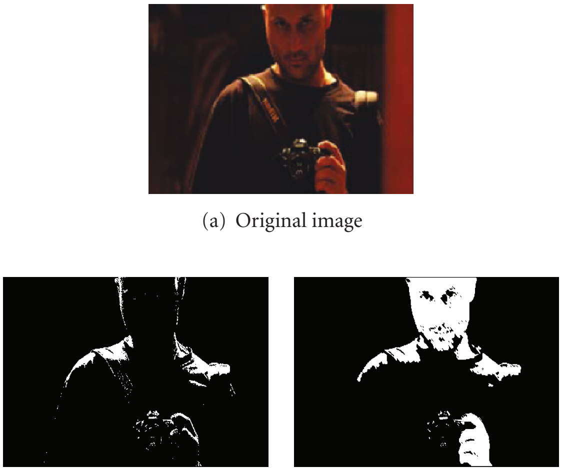
3. PERFORMANCE EVALUATION

In this section, we present the results that we got by simulating our proposed method along with some other existing methods for classification of skin pixels. We first describe the test data and the evaluation criteria that are used in comparison, and then we present some comparative assessments found from extensive simulations.

3.1. Experimental data

For statistics-based assessments, a large amount of data is needed. Here, we have used the Compaq skin and nonskin database [12, 21]. It includes a sufficient amount of skin as well as nonskin images. It has more than 14 000 images that consisting of almost 2 billions pixels. We randomly selected 4000 images containing skin regions and 5500 nonskin images to estimate the statistical models for simulating existing approaches, where necessary.

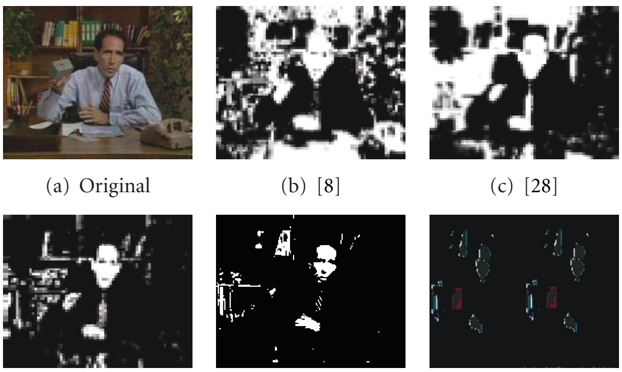
We have randomly picked up a test set of another 500 images comprising of 62,100, and 260 pixels, of which 9,859,733 are skin and 52,240,527 are nonskin pixels. We have used this test set to generate the various results in this paper. All the data in tables represent the average of the corresponding values found from simulation results on 500 test images.



(a) Original image

(b) Traditional RGB (c) Proposed method

Figure 5: Results of applying the methods on low illuminated image.



(a) Original (b) [8] (c) [28]

(d) [5] (e) RGB (f) Proposed

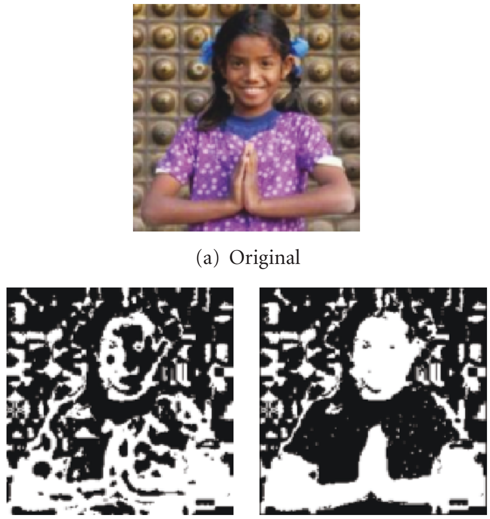
Figure 6: Results of applying various skin region extraction methods on salesman.

The Compaq skin and nonskin database also includes manually labeled skin masks for all skin images. These masks help a lot in building statistical models for skin. They also serve as ground truths in evaluating the detected skin regions.

Besides this database, we have also used the GTAV face database [16], the IBTD face database [22], and some other images collected from the Internet for visual assessment of the proposed method along with some existing ones.

3.2. Evaluation criteria

To evaluate the strength of the proposed method and to compare with other well-established proposals, we have calculated three different criteria as presented in [29]: correct detection rate (CDR)—percentage of skin pixels correctly classified, false detection rate (FDR)—percentage of nonskin pixels incorrectly classified as skin pixels, and overall classification rate (CR)—percentage of pixels correctly classified.



(a) Original

(b) [17] (c) Proposed

Figure 7: Results of applying existing HSI-based skin cluster classifier [17] and the proposed method.

3.3. Evaluation results

We have focused on some shortcomings of the currently available skin detection methods and propose our new approach to overcome them. We have experimentally found that the proposed method achieves very inspiring results. It is able to find clear skin segment in an image irrespective of ethnicity, background, and illumination conditions with high detection rate and less false detections.

In this section, we focus on several key observations of our experiments. The key findings are summarized and discussed as follows.

(i) *Segmentation:* Figure 4 shows some of the test results that we have found by applying the traditional RGB-based skin segmentation algorithm as well as the proposed one. Notice that the existing approach takes a number of scattered and noisy pixels as skin pixels. On the other hand, the proposed approach gives solid areas. This is because the existing method considers each pixel separately without using any other information. On the other hand, our approach makes use of the region information as well as color information (in the form of DM values). These help it to capture skin segments steadily without the inclusion of noisy pixels. Although in some cases it picks up some pixels from eye brows and hair regions, it can provide skin areas with confidence. Such results are useful especially as region of interest (ROI) in human-related image processing applications.

(ii) *Ethnicity:* our algorithm performs very well on the images having people from different races. Figure 4 shows such examples, which undoubtedly exhibits the superiority of the proposed algorithm over the traditional one.

(iii) *Low illumination:* Figure 5 demonstrates the outcome of the proposed and the traditional methods in low-light imaging condition. Here, the traditional method misses the face region, and the fingers are also not segmented properly. On the other hand, a better performance is done by the proposed method which is clearly noticeable. The main reason behind this is the usage of DM. The DM allows the method to go far, based on the input image condition, beyond the cluster specified by the original explicit skin cluster classifier.

(iv) *Complex background:* Figure 6 presents the performance of some existing skin segmentation techniques along with the proposed approach (using RGB space) on an image that contains complex background. Here, we use a frame of salesman video sequence. Figures 6(b)–6(d) are reprinted here from [5], since the authors of the respective methods are the best to set various parameters of their own algorithms. Figure 6 shows that our proposed technique extracts all skin regions. Moreover, it includes much fewer nonskin regions and noisy pixels than other methods.

(v) *Statistical analysis:* Table 1 shows the noticeable improvement done by the proposed one over the traditional RGB-based classifier. It shows, on an average, a good amount of increase in correct detection while decreasing the false detection rates.

Figure 7 presents an image of a girl from Indian ethnicity. Here, the background color is much closer to her skin color, making it difficult for skin segmentation. We apply a skin cluster classifier [17] based on HSI color space. We also apply our proposed method based on the heuristic rules of the same classifier. Figure 7 shows that our proposed method gives much better regions than the original classifier in [17].

In this connection, we claim that the proposed method based on any explicit skin cluster classifier yields better skin segments than applying the original classifier itself, especially in different imaging conditions.

Though our foremost focus in this paper is to improve the fixed threshold-based skin cluster classifiers, the proposed method also outperforms some other well-known approaches found in the literature. Describing these techniques in detail is out of scope of this paper. However, Table 1 presents the performance of some of them on our test data.

Phung et al. [29] analyze nine different skin detections approaches and conclude that the Bayesian classifier with histogram technique [12, 21] and the multilayer perceptron classifier [30] have higher classification rates. However, Table 1 shows a much better performance of the proposed method.

Bourbakis et al. [31] propose a skin color detection method using a neural network-based color consistency. Phung et al. [32] use Bayesian decision rule to classify skin pixels, and then filter out some nonskin segments using the edge and homoginiety information of the detected skin segments. Chenaoua and Bouridane [33] employ the principal feature analysis (PFA) which uses covariance matrix and eigenvectors to reduce the dimensionality of the color space. A Markov random field (MRF) is then used to model the distribution of skin colors. All these methods are clearly outperformed by the proposed approach as Table 1 presents. It shows the applicability of the proposed approach in real environments.

Table 1: Performance comparison in terms of detection rates.

Method	CDR (%)	FDR (%)	CR (%)
Traditional RGB-based method	81.2683	23.7099	77.0412
Proposed method	89.9749	9.2695	90.6165
Bayesian classifier [12, 21]	83.9234	10.9183	88.3034
Multilayer perceptron classifier [30]	83.3306	11.5401	87.6861
Classifier based on color consisty using neural network [31]	85.6037	10.6809	88.7585
Segment- and edge-based refinements of Bayesian classifier [32]	82.6245	10.4442	88.4416
PFA and MRF-based methods [33]	83.9304	10.8703	88.3453

4. CONCLUSION

In this paper, we have proposed a skin detection approach, which can be implemented using any explicit threshold-based skin cluster classifier in *any* color space. Though the algorithm mainly operates on a grayscale image (DM), the processing is actually done based on color information. The scalar distance map contains the information of the vector (color) image. This makes the method simple to implement.

Experimental results show that the proposed approach is better than applying the traditional threshold-based skin cluster classifier itself. We are pretty confident about its performance in different color spaces. Moreover, we have not used any strict threshold in the method, which makes it applicable in a variety of imaging conditions. We also make use of region information, which makes it robust against noisy pixels and generates solid skin area.

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