Adaptive Skin Segmentation Using Color Distance Map

Mohammad Shoyaib, M. Abdullah-Al-Wadud, and Oksam Chae

Abstract—In this paper an effective approach for segmenting human skin regions in images taken at different environment is proposed. The proposed method uses a color distance map that is flexible enough to reliably detect the skin regions even if the illumination conditions of the image vary. Local image conditions is also focused, which help the technique to adaptively detect differently illuminated skin regions of an image. Moreover, usage of local information also helps the skin detection process to get rid of picking up much noisy pixels.

Keywords—Color Distance map, Reference skin color, Region growing, Skin segmentation.

I. INTRODUCTION

SKIN region segmentation plays an important role in a variety of the human related image processing applications. In most of such systems it provides with some initial region-of-interest (ROI), which are further investigated by the later steps of a system. Such applications include human-computer interaction (HCI) based applications such as gesture analysis, facial expression detection, face tracking, human motion tracking etc., and other human-related image processing applications in computer vision and multimedia such as retrieval in multimedia databases, filtering of web contents, video-surveillance, videophone and videoconferencing applications etc. A successful detection of skin area increases system efficiency while false detections reduces it by engaging system resources for unnecessary analysis. Hence skin segmentation process should be effective enough to be *reliable* (should not miss any skin segment) and *precise* (should yield complete, not fragmented, segment without including noisy/non-skin segments).

Skin color is often invariant to orientation and size. If the underlying skin-color pixels can be represented, modeled and classified accurately, color information may be a very effective tool for identifying skin areas [6]. However, in 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, non-white lights etc., may cause change in skin color (color consistency problem [6]). Skin color also differs for different persons coming from different ethnic groups [14]. There are some other reasons that may also affect to make changes in skin color such as subject appearances (makeup, hairstyle and glasses), background colors, shadows, motions etc. For the abovementioned reasons skin color may show up as too bright or too dark. In such cases skin detection methods often detect nothing or fragmented skin regions or noisy/scattered pixels. Moreover, if different portion of the same image is differently illuminated (for lighting condition or people from different ethnicity), it becomes troublesome to detect all skin regions.

Existing methods for classifying skin and non-skin pixels are usually categorized into three broad categories: parametric, nonparametric and explicit threshold based skin cluster classifiers [6], [7]. Parametric methods consider that the distribution of skin color is clustered in a chromatic color space and can be represented by a Gaussian model [6], [8]. The parameters of the Gaussian model are set according a set of training pixels. However since the model is based on training data, it cannot handle different imaging conditions flexibly. Some mixture of Gaussian models considers different models for different luminance. For example, Phung [2] considers three while Wong [3] considers six separate groups along the luminance axis. These gives a better result in poor or strong lighting conditions, but in real life illumination change is more complex [1]. There are also some nonparametric methods that estimate skin color distribution from the histogram of the training data [13]. Such methods estimate a statistical model of the distribution of skin color by training the algorithm with a number of training data, which is a tedious task to perform. Moreover, it depends largely on the training set. This makes it applicable only in a limited range of imaging conditions. Explicit threshold base skin cluster classifiers are the simplest, and often applied methods [6], [7] to classify skin and non-skin pixels. These methods explicitly define the boundaries of the skin cluster in certain color spaces [7], [11-12], [15-20]. These techniques propose a set of fixed thresholds specifying some heuristic rules in a given color space. Such methods can be used right away without requiring any training phase. However, since these approaches are guided by some rigid values, they may lack of flexibility to work under different imaging

Mohammad Shoyaib is with the Department of Computer Engineering, Kyung Hee University, 1 Seocheon, Kiheung, Yongin, Gyonggi, South Korea, 449-701 (e-mail: shoyaib@khu.ac.kr).

M. Abdullah-Al-Wadud is with the Department of Industrial and Management Engineering, Hankuk University of Foreign Studies, 89 Wangsan, Mohyun, Cheoin, Yongin, Gyonggi, South Korea, 449-791 (e-mail: wadud@hufs.ac.kr).

Oksam Chae is with the Department of Computer Engineering, Kyung Hee University, 1 Seocheon, Yongin, Gyonggi, South Korea, 449-701 (corresponding author, phone: 82-31-201-2948; fax: 82-31-202-1723; e-mail: oschae@khu.ac.kr).

conditions. This may result in inaccurate classification of pixels.

To minimize the effect of change in imaging factors so that the image is less sensitive to the illumination, approaches are proposed to make use of color space transformation [11], [21-23] or ratios of different color channels [9-10]. It is generally accepted that chrominance is less affected by the change of illumination and skin colors of different people are very close. Hence some approaches remove the luminance component to represent skin color and use a "pure" color [1]. However, under significant change in illumination, skin color changes a lot, even for the same person [1]. In such cases some color information is also lost in the process of separating luminance from chrominance that may cause errors in the detection.

The main concern, therefore, is to define such skin cluster that can handle the change in imaging condition. However, existing skin models (whether built from training data or specified by heuristic rules) use strict values that may not change at run time in different conditions. Hence to make it applicable in different situations the cluster size need to be large enough, which also allows detecting more non-skin pixels as false positives.

To cope with the real-life variation in images, some dynamically adaptive skin color models/classifiers are proposed. Model updating [4], [5] is done by adapting the parameters of Gaussian model in face tracking. However, it incurs a risk of false adaptation, especially when tracking failure occurs. In general, such dynamic adaptation of skin model assumes that lighting condition changes smoothly over time so that the model can be updated based on the previous frame (video). Hence these are not suitable for unconstrained lighting conditions and still images. Zheng [1] detects one ground truth pixel from image based on a standard Gaussian model and then compensate the color with the help of another Gaussian model whose parameters are set for special illumination conditions. However, since color is compensated based on one pixel, same compensation ratio is applied for all pixels in the image. It may not handle differently illuminated parts of the image differently.

For the lack of flexibility in different imaging conditions, even with the color compensation methods, existing skin detection methods often detect nothing or fragmented skin regions or noisy/scattered pixels. Moreover, skin segmentation approaches, as a whole, aims at segmenting 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, they may provide with noisy pixels, and incomplete or partial segments. Therefore, more sophisticated approaches are still required to overcome this skin color inconsistency problem.

In this paper, an adaptive skin color segmentation approach is proposed to work under changing and mixed illumination. It handles differently illuminated parts of an image more closely to detect different skin appearance due to ambient lights, different races etc. The method basically runs using an existing skin cluster classifier and provides enhanced performance in varying imaging conditions. A Reference skin color (RSC) is used, based on which a color distance map (CDM) is generated. The CDM itself is a grayscale image making the procedure simple enough while it still contains the color information too. Besides, the CDM can reliably be generated without prior knowledge about current image. Moreover, close investigation on different skin regions on an image the proposed approach uses neighborhood information to yield solid skin segments and not to pick up noisy pixels.

The rest of the paper is organized as follows: Section II presents some related terminologies used in this paper while Section III presents the proposed approach. Performance of this approach is presented in Section IV and Section V concludes the paper.

II. Terminologies Used in this Paper

A. Reference Skin Color (RSC)

The Reference Skin Color (RSC) is a color that certainly represents a skin color. Usually it represents the center point of skin cluster in a certain color space. It is denoted as a vector $(C_{1_s}, C_{2_s}, ..., C_{n_s})$, where C_i denotes the color coordinate and n is the dimensionality used to specify skin cluster in a color space. For example, the RSC 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 co-ordinates $[C_{1_{start}}, C_{1_{end}}], [C_{2_{start}}, C_{2_{end}}], ... [C_{n_{start}}, C_{n_{end}}]$, then the corresponding Reference Skin Color (RSC) will be defined as $\left(\frac{C_{1_{start}}, C_{1_{end}}}{2}, \frac{C_{2_{start}}, C_{2_{end}}}{2}, ..., \frac{C_{n_{start}}, C_{n_{end}}}{2}\right)$. If skin cluster is approximated by Gaussian distribution, then the mean of the distribution may serve as RSC.

B. Color Distance (CD)

Color Distance (CD) is defined as the Euclidean distance between a certain color and RSC. Mathematically, CD of the color $(C_1, C_2, ..., C_n)$ is $\left|\sqrt{\sum_{i=1}^{i=n}\left(C_i - C_{i_s}\right)^2}\right|$. For example, CD of color (R, G, B) is $\left|\sqrt{(R-R_S)^2 + (G-G_S)^2 + (B-B_S)^2}\right|$.

C. Color Distance Map (CDM)

Color Distance Map (CDM) [24] 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, i.e., [0, 255]. In some cases, however, CDM generation may not be such straightforward when —

i. A classifier defines more than one skin cluster in certain color space, i.e., there will be more than one RSC as well.

ii. The decision making criteria includes some constraints/condition checking rather than specifying a range of color values only.

To handle the first problem, one RSC is defined for each skin

cluster and create an initial CDM for each of them. Then the final CDM is generated by taking the smallest CDs at corresponding positions among initial CDMs (Eq. 3 provides an example of this). In other words, the final CD of a pixel is the minimum of its CDs in the initial CDMs. Hence the CD corresponds to the closest skin cluster of that pixel color. Thus a single CDM ensures to represent all the skin clusters specified by the classifier.

The second problem can easily be handled by specifying the maximum possible CD for the pixel color that fail to satisfy the conditions/constraints.

Here one simple and classical RGB color space based classifier [7], [16] is presented as an example. It takes two different conditions (involving strict thresholds) into account: uniform daylight and flash or lateral illumination.

Uniform daylight illumination:
$$R > 95, G > 40, B > 20$$
$$Max\{R, G, B\} - Min\{R, G, B\} > 15 \qquad (1)$$
$$|R - G| > 15, R > G, R > B$$

Flashlight or daylight lateral illumination:
$$R > 220, G > 210, B > 170 \qquad (2)$$
$$|R - G| \leq 15, B < R, B > G$$

It classifies a pixel as skin only if either of these two set of conditions is true. Throughout this paper this method is referred to as "Traditional RGB based method/algorithm".

At first, RSC is set as the middle of the skin cluster specified by inequalities in first line of Eq. (1), i.e., (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 second and third line of Eq. (1), are then set to 255. Thus, a grayscale image, Map_1, is achieved according to Eq. (1). Using the same strategy, another image, Map_2, is generated following Eq. (2). Then they are combined into a single CDM, M, according to Eq. (3).

$$M(x, y) = Min\{Map_1(x, y), Map_2(x, y)\} \qquad (3)$$

where (x, y) represents pixel position in image.

Eq. (1) and Eq. (2) defines two skin clusters in RGB color space. By taking the lower distances between these two, Eq. (3) assures to represent the distance to the closer cluster. Hence the CDM is consistent with both conditions defined by Eq. (1) and Eq (2).

Here some properties of CDM are mentioned.

Property 1. CDM represents skin likelihood of pixels regardless the number of skin clusters specified by the classifier.

CDM represents the prospect of each pixel to be taken as skin (as well as non-skin) pixel. The lower the value, the higher (lower for non-skin ones) is the possibility. This property enables a single CDM 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 initial

CDMs is considered, it represents the prospective skin cluster it may fall into).

Property 2. CDM contains color information.

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

Property 3. The distribution of CDs of skin-pixels in any image is approximately Gaussian (more specifically, right half of Gaussian since absolute values are taken in calculating the CDs) if RSC is carefully chosen.

To investigate the correctness of *property 3*, Compaq Skin and Non-Skin Database [28], [30] and IBTD face database [26] are used. These databases provide skin masks along with the original images. 300 and 200 skin masks are randomly selected from the Compaq Skin and Non-Skin Database and IBTD face database, respectively. Some images are also taken from the GTAV face database [25] and the Internet, and then manually segmented skin regions in those images. For these skin regions, CDMs are produced and histograms of CDMs are generated. They are then tested statistically, using the well known Jarque-Bera test [31-33], whether the distribution of the CDs falling at the right side of RSC is half of Gaussian. Skin regions of all test images were found to pass the test.

III. THE PROPOSED METHOD

Skin detection in an image using color information usually involves two major steps: to represent the image pixels in a suitable color space, and to classify the skin and non-skin pixels using an appropriate distribution model.

Generally, it is agreed that there is no single color system, which is suitable for all color images [23]. Therefore, insisting on the adoption of specific color system to be used in the skin classification algorithm is unnecessary [18]. Hence, any specific color space is not strictly followed here. At times RGB space is used as an example only. Our focus is mostly on the skin and non-skin pixel classifier. A flexible skin segmentation method is proposed, which can adapt with some changes in imaging conditions in different skin areas in an image.

Handling vector (color) images and defining skin clusters in color spaces is a complicated task, especially in different imaging conditions. On the other hand handling scalar (grayscale) images is much simpler, but it faces lack of information to perform the job acceptably. Hence it will be advantageous to use color information for confident decision making and at the same time work on grayscale images for simpler operations. Moreover, skin clusters that are defined either by explicit thresholds or by training dataset may not provide any flexible behavior to move the position in the color space. Hence it may not detect some skin areas in different imaging conditions. Hence an amendable skin cluster is more desired to perfectly fit the skin clusters in any desired condition.

Our proposed method mainly uses a color distance map (CDM) [24], which itself is a grayscale image, but still containing the necessary color information. Moreover, it can

tune itself with the change of imaging conditions.

The proposed technique first selects an existing skin cluster classifier. Starting from there, it searches for a Reference Skin Color (RSC), 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 (CDM) based on which some portion of skin regions are generated. The algorithm then closely looks into these partial skin regions to detect complete skin segments. Fig. 1 presents an outline of the proposed approach for skin detection. The total approach is described in the following subsections.
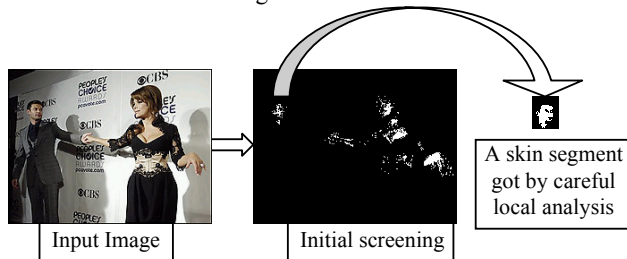

Fig. 1 An overview of the proposed approach

A. Selecting Reference Skin Color (RSC) Adaptively

To handle various situations, an adaptive technique is proposed to select RSC based on input image. The third property of CDM (in Section I) states that the grayscale values in CDM of skin regions of an image have right half of a Gaussian distribution. Hence if the RSC can be perfectly chosen, the corresponding CDM can have the distribution of CDs fitted with the right half of an approximately 0 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, a distribution like right half of a 0 mean Gaussian distribution may not occur. In such cases it will fit with right half of a μ-mean (say) Gaussian, which means the RSC may be expected to be somewhere very close to the colors having CD μ. Hence what can be done is to redefine the RSC with the average of pixel colors having CD μ and regenerate the CDM. Here this new RSC will shift μ to a lower value. Iterating this process will eventually lead to a μ close enough to 0.

Property 1 of CDM mentions that the CDs of skin pixels are very small compared to the non-skin ones. Combining property 1 and property 3 of CDM, it may be expected 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 CDM. To search for such distribution, the first significant maxima (possibly the mean, μ) in the histogram and first significant minima (possibly the end of the distribution, Th) after μ are searched. If the histogram components in the range $[\mu, Th]$ successfully pass a test of Gaussianity, then it may be expected to represent skin regions. Otherwise, the image (or the corresponding portion of image that generated the CDM) may be declared not to have skin region in it.

An initial RSC and CDM are generated first as mentioned in the previous section. The RSC (as well as the CDM) is then refined according to the algorithm in Fig. 2. It also uses the Jarque-Bera test [31-33] of Gaussianity.

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Algorithm Find_RSC()

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

Output parameter
C : The refined RSC for this image

Procedure
1. Set μ = first significant local maximum in H.
2. Set Th = first significant local minimum in H, where Th > μ.
3. If components of H in [μ, Th] is close to right half of Gaussian then
4.     If Th < ε then
5.         Return C.
6.     Else
7.         Set C = Average of color of pixels whose CD is μ
8.             Generate a new CDM, M, with respect to C
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
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Fig. 2 Algorithm to refine RSC

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

In most images, it needs to iterate the procedure twice or thrice only. It also advocates for the efficiency of this RSC selection to be used in real world applications.

B. Global Inquiry: Initial Screening

The purpose of this step is to select some pixels, which undoubtedly represent skin, from each skin region of the image. The straightforward way (in ideal cases) is to select the pixels having RSC. 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 RSC. A thresholds T, which represent the first significant local minimum of the histogram of CDM, is taken. Here T is not rigid as well (the local minima may vary for different images). The seeds for skin regions are then generated using algorithm in Fig. 3. The rest of the pixels are treated as undefined pixels to be determined in the later step.

Due to the refinement of RSC selection, it may be assumed here that some pixels from each skin region are selected at this step. These are the seed regions from where the close analysis of the regions starts. However, this selection procedure works well under the assumption that *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. To

make this approach more flexible to handling variation in this assumption needs further analysis. This is left here for future investigation.

Algorithm Find_Seed()
Input Parameters
T : A low threshold.

Procedure
1. **If** $M(i, j) \leq T$ **then**
2.   The pixel at position (i, j) is a skin pixel.
4. **Else**
5.   The pixel at position (i, j) is undefined.

Fig. 3 Algorithm for determination of skin seeds from distance map

C. Local Analysis: Investigation of Seed Regions

Due to ambient lighting, shading, existence of people from different races (or different skin area of same person) in an image etc., appearance of skin may vary in different position of the same image. In such cases a global color compensation such as greyworld [34] or model updating [1] may not provide with satisfactory output. This is because of lack of handling the variation local image condition.

Algorithm Detect_Skin_Regions()
Procedure
1. Generate the CDM based on a general RSC according to what is presented in Section I.
2. Refine the RSC according to Find_RSC procedure presented in Fig. 3.
3. Regenerate the CDM.
4. Take the pixels up to the first significant local minimum. It generates portion (seed) of skin areas.
5. Label the skin regions.
6. Take a block of interest (a rectangle larger that the one that fits the region) around each labeled region.
7. For each such block, apply the following procedure recursively. Let us suppose that RSCo is the Reference Skin Color based on which this region (seed) was generated.
   a. Generate color distance map based on RSC$_o$.
   b. Select an RSCn based on analysis of Gaussian distribution similar to what is presented earlier in Fig. 3.
   c. Regenerate the distance map.
   d. Take the pixels up to the first significant local minimum in the histogram.
   e. If no new skin pixels is accounted, then
      Stop the recursive call for this region.
   f. Otherwise
      Repeat step 5, 6 and 7 recursively (using RSCn).

Fig. 4 Complete algorithm of the proposed approach

The purpose of this step is to make use of the seed regions to capture the whole skin segment. To do so, an iterative algorithm is used that works separately on each seed region. For each region, a bounding rectangle is taken. The iterative process is then started with the distance map that is already created. The process similar to Section II(B) and Section II(C) is then applied to select a new RSC based on the seed pixels of this particular region only, generate a color distance map and take the pixels up to a threshold (first significant local minima). All the pixels up to this threshold are taken as skin pixels. If no new skin pixel is found, the iteration stops for this region. Otherwise all seed region go through the same procedure to find new skin pixels in their respective bounding box. If any

new skin pixel is encountered on the boundary of the bounding box, then the boundary is shifted to let the region grow freely.

Here each iteration is totally based on the local information which is free from the influence of other potion of the image even if they are differently illuminated. The complete algorithm is presented in Fig. 4.

IV. PERFORMANCE EVALUATION

The GTAV face database [25], the IBTD face database [26] and Compaq Skin and Non-Skin Database [28], [30] are used to evaluate the performance of the proposed algorithm. These databases have a good collection of images taken at many different imaging conditions. Some images collected at our own from the Internet during last few years are also used.

(a) Original Image   (b) Traditional RGB   (c) Proposed method
Fig. 5 Results of applying the methods on low illuminated image

Fig. 5 demonstrates the outcome of applying the proposed as well as the traditional method on a low-light image. Here the traditional method misses the face region and the fingers are also not segmented properly. On the other hand a better performance done by the proposed method is clearly noticeable. The main reason behind this is the usage of CDM. More specifically, it is due the adaptive selection of RSC. The proposed method allows going faraway, based on the input image condition, beyond the cluster specified by the original explicit skin cluster classifier.

(a)

(b)

Fig. 6 Some images showing the results of applying the traditional RGB based method and the proposed method. In each set, the first, second and third images represents input image, image after segmenting using traditional RGB based method and the proposed method, respectively

Fig. 6 shows some of the test results, which has been got applying the traditional RGB based skin segmentation algorithm as well as the proposed one. Here it can be noticed 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 explicit thresholds define a large skin cluster in color space to capture skin colors in some variety of conditions. Hence it is very much likely to capture some skin like non-skin objects as well. On the other hand, thresholds in the proposed method are totally data driven and less likely to include non-skin pixels due to the Gaussianity test. Moreover, 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 CDM values). This helps it to capture skin segments steadily without including noisy pixels. Although in some cases it still includes some neighboring non-skin pixels, it can provide confident skin areas. Such results are useful especially as region-of-interest (ROI) for human-related image processing applications.

Fig. 7 shows the outcome of some existing skin segmentation techniques along with the proposed approach (using RGB space) on an image that contains complex background. Here a frame of *Salesman* video sequence is used. Fig. 7(b)-(d) are reprinted here from [11], since the authors of the respective methods are the best to set various parameters of their own algorithms. Fig. 7(e) shows the outcome of explicit threshold based classifiers, which has not captured all the skin regions completely (notice the right hand). On the other hand our proposed technique extracts all skin regions. This is due to the close and iterative analysis of each region. Moreover, it includes much fewer non-skin regions and noisy pixels than other methods.

(a) Original   (b) [5]   (c) [19]

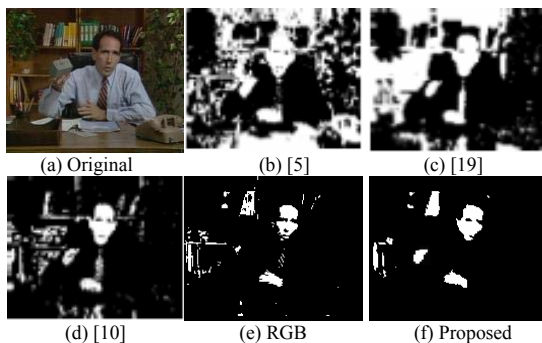(d) [10]   (e) RGB   (f) Proposed

Fig. 7 Results of applying various skin extraction methods on *Salesman*

To verify the performance of the proposed method numerically in terms of correct and incorrect classification rates, the IBTD face database [26] is employed. This database has a large collection of skin images of various skin types, poses, background and lighting conditions. Moreover, it provides hand-segmented skin regions of these images, which may serve as ground truth for verification of skin detection algorithms.

500 images are picked from the IBTD face database at random and applied our proposed algorithm on them. For each image, three different values [27] are then calculated: 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. Average of these three terms is calculated to find the overall effectiveness of the approach. For the proposed approach, these quantities are 90.04%, 9.86% and 91.23% respectively.

[27] analyzes nine different skin detections approaches and summarizing their performances, it concludes that Bayesian classifier with histogram technique [28] and multilayer perceptron classifier [29] have higher classification rates. However, allowing FDR to be 10%, their CDRs are approximately 83% (approximated from the ROC curve presented in [27]), while it is 90.04% for the proposed one with FDR being 9.86%. On the other hand the maximum CRs achieved by these two approaches are 89.79% and 89.49% (which are 88.75% and 88.46% if FDR is 10%) respectively, whereas it is 91.23% for our proposed approach. These results also show the applicability of the proposed approach in real environment.

V. CONCLUSION

In this paper, an adaptive skin detection approach is proposed to detect differently illuminated skin regions in an image. It can be applied using *any* skin cluster classifier. Though the algorithm mainly operates on a grayscale image (CDM), the processing is actually done based on color information. The scalar CDM contains the information of the vector (color) image. This makes the method simple to implement. Detail analysis of each skin region is also employed, which makes it robust against noisy pixels and assists to generate solid skin area.

Experimental results show that the proposed approach is better than applying the traditional classifiers. Authors are pretty confident about its performance in different color spaces. Moreover, no strict threshold as well as no strict range of values is used in the process. This makes it applicable in a variety of imaging conditions.

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