Comprehensive Evaluation of the Pixel–Based Skin Detection Approach for Pornography Filtering in the Internet Resources

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***Abstract*— A robust skin detector is the primary need of many fields of computer vision, including face detection, gesture recognition, and pornography filtering. Less than 10 years ago, the first paper on automatic pornography filtering was published. Since then, different researchers claim different color spaces to be the best choice for skin detection in pornography filtering. Unfortunately, no comprehensive work is performed on evaluating different color spaces and their performance for detecting naked people. In this way, researchers refer to the results ion skin detection for face detection, which underlies different imaging conditions. In this paper, we examine 21 color spaces in all their possible representations for pixel–based skin detection in pornographic images. In this way, this paper holds the largest investigation in the field of skin detection, and only one run on the pornographic images.**

***Index Terms*— Pornography Filtering, Skin Detection, Content Based Image Retrieval, Color Modelling, Color Image Processing.**

I. Introduction

With the rapid penetration of the Internet into every part of our daily life, it is agreed that it will be an important media for future communication, perhaps even more important than the television [1]. Though, it is proved, even for non–regular users of the Internet, that it is getting more and more contaminated with harmful content, such as pornography, violence, hatred and so on. In a recent survey, one in four kids reported having at least one unwanted exposure to sexually explicit pictures during the past year, and one out of five reported receiving a sexual solicitation [2]. Recent statistics reveal that 25% of the queries in search engines, 8% of emails, and 12% of homepages are porn–related [3]. Also, the average age of first internet exposure to pornography is 11 years old [3].

While parents and educators tend to have more control on the information exposed to their children when surfing the web, the common textual approach (such as *NetNanny*, *CyberSitter*, and *SurfWatch*) is not performing well [4]. While failing to give enough immunity, the text–filtering approach blocks many useful sites, just because of the presence of some certain phrases. For example, a commercial package blocked the White House children's page in 1996 [5]. On the other hand, the owners of the harmful sites are inventing new methods for shutting down the text–searching immunity system. Approaches like only–picture pages and safely–named files are now just common. In recent years, the pictorial content–based filtering is gathering more and more attention.

A rapid review of the available content-based pornography detection approaches (see Section II-A) reveals that they are all essentially based on detecting skin areas in the images. Also, a more careful review shows that the frequently applied methods for skin detection are pixel–based approaches using ordinary or Baysian look–up tables. According to the number of available color spaces and the diversity of the choices made in the literature, it is clear that a through investigation of the performance of different color spaces for this problem is mandatory. In this paper, we examine 21 color spaces in all their possible representations. The examination is aimed on evaluating different color modelling approaches in terms of their performance on skin detection in pornographic images.

II. Literature Review

A. Content–based Pornography Filtering

The first work on classifying nude pictures belongs to *Forsyth et. al.* [6]. In that approach, firstly, the images containing large areas of skin are detected (using IR_gB_y color space) and then using a specially defined human structure [7], the images containing human figures are recognized as the nude ones. In their approach, only the images which are at least covered in one third by the skin area are fed to a geometric analyzer. While all the images used in [6] are 128×192, it takes about six minutes for the method to process a single image. Though, the final recall of the method is less than 50%.

After that, other researchers made new contributions in this field. In [8], the researchers utilize skin detection in RGB color space equipped with wavelets and central moments on 128×128 images to develop the WIPE^{TM} system.

In [9], the researchers combine the results of a simple skin area estimator based on a skin detection filter with textual analysis results. That paper reports that "*while a threshold is selected, the choice of the color space is not critical. This is somewhat surprising because other authors advocate the use of IR_gB_y*". That work is extended in [10] using a specific neural network to raise the recall rate up to 90%. The researchers draw the final conclusion that "*provided that enough training data and a histogram–based representation of the color distribution are used, then the choice of color space is not critical*" [10].

In [11], the authors describe the steps towards developing an adult image detection scheme using the skin color in YUV,

YIQ, and their polar representations ($YUV°$, $YIQ°$). In that approach, a *Sobel* edge detector and a *Gabor* filter judge the results of the skin detector. In [12] the researchers use $CIE-Lab$ color space for detecting the skin areas in the images. The results are then analyzed using some geometrical features.

In [13], the researchers compute some shape descriptors using the results of skin tone detection in YC_bC_r and IR_gB_y. Then, using an Adaboost learning scheme, the erotic images are classified. In [14], the researchers combine the results of a neural network classifier working on image features with a commercial text–filtering tool developed by *SurfWatch* (used by *Altavista*). The image feature used in that work only relate to the portion of pixels identified to be skin (in RGB color space), with no further geometric processing.

The skin detector in [15] is used in [16] to develop a MPEG7–based adult image identification system, using query–based search into an erotic dataset. In the approach described in [17] the results of a skin detector in RGB and HSV color spaces are used to produce other features like a simple texture descriptor. Then, all of the features are fed to a *state vector machine* (SVM). In [18], the researchers use the results of a straight skin–detection rule ($R > G$ or $R > B$) with a SVM classifier.

In [19], a gaussian mixture model is equipped with Baysian inference to utilize the skin detection stage. Then, the results are fed to a SVM. In [20], the researchers utilized genetic algorithm for locating the loci of nude pictures in a search space containing huge 801–D feature vectors. Each feature vector contains color histograms in the C_b and C_r color components plus some shape descriptors. Alongside using the color components' histograms in the feature vector, the method in [20] devises hard thresholds on the C_b and C_r components to extract the skin–like objects ($78 \leq C_b \leq 135, 85 \leq C_r \leq 185$). In [21], the researchers use the results of a skin detector in the RGB color space for a multi–layer perceptron classifier. In extended works they applied a better skin detection filter developed in [15]. In [22] researchers utilize a custom non–linear color space. In [23] a multi–Baysian skin detector is utilized. Note that in this survey, similar works of authors published in different places are represented by a single citation.

B. Skin Detection

From the review in Section II-A, it is clear that it is generally accepted that the first step towards finding the whole human body or its selected parts is to find those parts of the image holding pixels corresponding to the skin material. This assumption is theoretically backed by models of the skin tissue. In this way, it is argued that the color of human's skin is created by a combination of blood (red) and melanin (yellow, brown) [24]. Most researchers presume from these evidence that the skin color can be recognized in an image with no explicit knowledge about the lighting conditions, the camera calibration, and the subject properties such as the race.

A skin detection system consists of two major parts. First, there should be a proper model for representing colors, what we call the color space. Second, there is an inference methodology to obtain information from available skin samples and to extrapolate the results to given samples. For the first part, a rapid investigation of the literature shows that the solution of different researchers seems to be more related to personal taste rather than experimental evidences [25]. We will discuss this point with more details in this paper.

While there are plenty of methods for modelling and detecting skin tone in pornography detection field, researchers tend to gather around two major choices. From the twenty–six available approaches for pornography detection, sixteen use ordinary look–up table, seven use Baysian look–up table, and only three utilize a different approach for skin detection. Hence, here we focus on the two methods for look–up–table–based skin detection. As such, the concentration of this paper is on the best choice for representing color vectors.

Few works are available that compare the performance of different color spaces for skin detection (*e.g.* see [26], [27], [28], [29], but they are all concerned with face detection. As mentioned in [30] "*pixel–based skin detection has long history, but surprisingly few papers that provide surveys ... were published*". for a survey of the available color space comparison works see [30]. We argue that as the conditions for pornography filtering are essentially different from other skin–related fields that allow more–or–less constraints on the imaging conditions, a more precise and focused investigation in this field is necessary.

The contributions of this paper are in three ways. Firstly, here we use all our samples and training data from pornography resources. In this way, we concentrate on the best choice of color space for pornography detection. In this way, this research is dedicated to detecting skin tone in pornography images taken in absolutely arbitrary conditions. Secondly, we arrange the largest number of color spaces ever used in an evaluation. While the available works compare less than ten color spaces with each other, we gather 21 color spaces in a unique experiment. The third contribution of this work is that we make no presumptions about the best dimension of color spaces. All available works use the original 3–D color spaces, or cut them into 2–D representations by neglecting the component assumed to be related to illumination. In contrast, we perform all the experiments on each color space in all its possible 3–, 2–, and 1–D representations. Also, more than computing the performance of different color models for the training and test data, we perform a real skin detection task for a large erotic dataset and evaluate different color space sin terms of corresponding results.

III. Proposed Method

Assume that we are working in the color space $c_1c_2c_3$. Also, assume that c_1, c_2, and c_3 are linearly scaled and biased to give values in the interval $[0, 255]$ (8–bit representation). The pixel–based skin detection approach presumes that there exists a function $P : [0, 255]^3 \rightarrow [0, 1]$ for which, $P(\vec{c})$ shows the probability of $\vec{c}$ belonging to a skin–related area. The function P is also called the *skin probability map* (SPM) [29], [27]. Generally, P is cut by a fixed threshold to obtain a binary look–up table.

There are two general approaches for finding P, *ordinary look–up table* (OLUT) and *Baysian look–up table* (BLUT).

Section III-A presents the color spaces included in this investigation, and Section III-B and III-C discuss the two methods for computing P. Finally, Section III-D proposed a method for detecting the skin map using a proper LUT.

Note that, some researchers try to code the LUTs using simple geometric rules [31]. For example, rectangles, set of planes, and ellipses are being used. We emphasize that those approaches are simplified versions of the general LUT–based skin detection process discussed here. As, for explaining the skin–tone locus by a set of geometric rules in the color domain, one first should prove that such locus exists.

A. Color Spaces

In this work, we use the twenty one color spaces of RGB, $HMMD$ (as the 3–D space HMM), HSI, HSV, $I_1I_2I_3$, $CIE-XYZ$, $CIE-Luv$, $CIE-Lab$, $CIE-LHC$, $YC_bC_r, YIQ, YUV, IR_gB_y, IR_gB_y^+, Nrgb, YUV^\circ, YIQ^\circ$, $YCbCr^\circ$, HSI^c, HSV^c, $RGBr$, and TSL. To make the range of different color spaces comparable, they are all normalized to the $[0, \cdots, 255]$ interval.

An arbitrary color space $x_1x_2x_3$ may be seen in 7 representation of $x_1x_2x_3$, x_1x_2, x_2x_3, x_3x_1, x_1, x_2, and x_3. In this way, we examine all possible representations of each single color space. Here, we add the name of the color space before its components (when necessary) to avoid mistakes. For example, the I component in YIQ is called $YIQ.I$, while the I component in IR_gB_y is called $IR_gB_y.I$. When this is unnecessary, the original names are used, for example I_3 in $I_1I_2I_3$ is easily addressed as I_3.

B. Ordinary Look–up Table (OLUT)

The ordinary look–up table–based skin detection approach assumes that the SPM can be estimated from a proper training set. This approach is quite commonly used in the literature (*e.g.*, see [32], [33], [34], [28], [35], [36], [37], [38], [14], [20], [13], [11], [21], [17], [8], [6]).

Here, we investigate the validity of this assumption. Assume that we have two sets of 3–D vectors, relating to skin and non–skin (control), respectively. Also, assume that there are N_s pixels deliberately extracted from skin area and N_c pixels which do not represent skin. Both N_s and N_c should be large enough. In our case, we had $N_s = 278530$ and $N_c = 192514$. Now, assume that H_s denotes the p–D histogram of all skin samples in an arbitrary color space ($p = 1, 2, 3$) (H_c is computed for the control dataset in a similar way). By setting different values of p we are able to remove one or two of the components of a color space. For computational purposes we select the number of bins in each direction equal to 16, 64, and 256 for 3–, 2–, and 1–D representations, respectively.

The main assumption behind the validity of OLUT–based skin–detection is that H_s can serve as P, the SPM. In this way, for an arbitrary threshold value θ, all color vectors $\vec{c}$ that satisfy $P(\vec{c}) \geq \theta$ are regarded as skin samples. Due to the fact that the summation of all elements of H_s equal unity, the elements of H_s may be too small. Thus, setting $P(\vec{c}) = H_s(\vec{c})$ will result in difficulties in selecting θ. To make the range of feasible values of θ more appropriate, we compute P as,

$$P(\vec{c}) = \frac{H_s(\vec{c})}{\max_{\vec{d}}\{H_s(\vec{d})\}}. \tag{1}$$

In this way, θ can accept all values in the range of $[0, 1]$ [28].

For an arbitrary value of θ, the OLUT is a binary array with a size similar to H_s and H_c. Zero element in the $\vec{c}$ bin means that $\vec{c}$ does not represent skin tone, while unity indicates skin. Then, the *true positive* (TP) and *false positive* (FP) values are computed as,

$$TP = \sum_{\vec{c} \in [0,L]^p} H_s(\vec{c}) LUT(\vec{c}), \tag{2}$$

$$FP = \sum_{\vec{c} \in [0,L]^p} H_c(\vec{c}) LUT(\vec{c}). \tag{3}$$

Clearly, we expect a value of θ resulting in a TP of around unity and a FP of around zero. Note that FP and TP are always between zero and unity.

For an arbitrary color space and a value of p, by selecting different values of θ in the $[0, 1]$ interval, we compute a set of corresponding (TP, FP) pairs. When these pairs are drawn in an axis, we reach to the *receiver operator characteristics* (ROC) curve. This curve is a keen way to determine an appropriate value of θ.

C. Baysian Look–up Table (BLUT)

Assume that a color vector $\vec{c}$ is given. Note that, what we actually need is $p(skin|\vec{c})$. From the Bayes theory we know that,

$$P(skin|\vec{c}) = \frac{P(\vec{c}|skin)p(skin)}{P(\vec{c}|skin)p(skin) + P(\vec{c}| \sim skin)p(\sim skin)}, \tag{4}$$

where $p(skin)$ and $p(\sim skin)$ are *a priori* probabilities, which are absolutely unknown. Here, $p(skin)$ and $p(\sim skin)$ are the probabilities that an arbitrary pixel represents skin and non–skin tones, respectively. Now, we write down the Bayes equality for $p(\sim skin|\vec{c})$ as,

$$P(\sim skin|\vec{c}) = \frac{P(\vec{c}| \sim skin)p(\sim skin)}{P(\vec{c}|skin)p(skin) + P(\vec{c}| \sim skin)p(\sim skin)}. \tag{5}$$

Note that,

$$P(skin|\vec{c}) + P(\sim skin|\vec{c}) = 1. \tag{6}$$

as trivially expected.

Using (4) and (5) we have,

$$\frac{P(skin|\vec{c})}{P(\sim skin|\vec{c})} = \frac{p(skin)}{p(\sim skin)} \times \frac{P(\vec{c}|skin)}{P(\vec{c}| \sim skin)}. \tag{7}$$

Here, we define two notations:

$$p^-(\vec{c}) = \frac{P(\vec{c}|skin)}{P(\vec{c}| \sim skin)}, \tag{8}$$

$$p^+(\vec{c}) = \frac{P(skin|\vec{c})}{P(\sim skin|\vec{c})}. \tag{9}$$

Note that according to (7), we have,

$$p^+(\vec{c}) = \frac{p(skin)}{p(\sim skin)} \times p^-(\vec{c}). \tag{10}$$

Using the normalization scheme used in (1), we have,

$$\frac{p^+(\vec{c})}{\max_{\vec{d}}\{p^+(\vec{d})\}} = \frac{p^-(\vec{c})}{\max_{\vec{d}}\{p^-(\vec{d})\}}, \tag{11}$$

which eliminates the two unknown probabilities of $p(skin)$ and $p(\sim skin)$. In fact, $p^-(\vec{c})$ is computed using two proper datasets of skin and non–skin, and (11) enables us to use it for creating a BLUT. From this point, everything is just similar to what performed in the OLUT–based skin detection process, described in Section III-B. This approach is used in [9], [10].

D. Skin Map Computation

Assume that we have the p–D color space X in which H is presumed to be a proper LUT for skin detection. Assume that H is a b^p–bin histogram. For the given image I, the process of finding its corresponding SPM is straightforward: compute J, the representation of I in X. Then, for each single pixel $\vec{c}$, compute the corresponding bin in H. Now, $\vec{c}$ represents skin iff the corresponding bin in H holds unity. This process results in the binary image M (M and I are in the same size). For the sake of simplicity, we propose another version of this scenario. For $0 < \lambda < 1$, first compute I_λ as the resized version of I with ratio λ ($\lambda = 10\%$ is a proper choice). Then, compute the SPM for I_λ as described above. Lets call the SPM of I_λ as M_λ. Now, up–sample M_λ, with ratio $\frac{1}{\lambda}$, to reach to M (which is the same size as I). According to the performance of MATLAB in processing arrays, and its deficiency in working with "*for*" loops, the above scheme gives considerably higher speed (about 4 times). The choice of the upsampling method depends on the expected quality of results; for fast evaluation the nearest neighborhood is a proper choice while bi–linear gives smoother results in cost of higher computational complexity.

IV. Datasets

Using the *Google* advanced image search with enabled "*large size*" option and some erotic keywords, 2284 pornographic images were downloaded. Some of the images came from amateur weblogs devoted to pornography. All images are in color, represented in RGB color space and compressed using the standard *jpeg* compression with high visual quality. After the images are downloaded from the net, no preprocessing is performed on them. These images produce a dataset of erotic images. Both indoor and outdoor images of single and multiple people with both complex and simple backgrounds are collected in the dataset. It includes photographs of female Hollywood stars, professional photographs of erotic models, amateur pornographic images, and pictures taken in the beach.

The skin area of some of the images of the erotic dataset are cropped manually. The cropped images are then resized to 64×64 pixels. As such, a new training dataset of 314 samples is generated, which is called the skin dataset. Another dataset of 106 patches, each containing pixels corresponding to a single material is also produced. The patches are selected manually from images taken by a *Canon A60* digital camera at daylight with flash. This dataset is used as the control data.

V. Experimental Results

The experimental results are carried out in a 2046MB PIV processor using MATLAB 6.5 and image processing toolbox 3.2.

The ROC curves of the OLUT–based skin detector for the 21 color spaces under examination reveal several interesting features about the color spaces and their performance in OLUT–based skin detection. Firstly, selecting those color spaces resulting in points in the ROC, satisfying $TP > 90\%$ and $FP < 10\%$, results only in RGB, $HMMD$, $I_1I_2I_3$, I_2I_3, HSI, HSV, $HSV.HS$, VH, C_bC_r, YC_bC_r, IQ, $YUV.UV$, $CIE{-}Luv$, $CIE{-}uv$, Nbr, UV°, IQ°, $C_bC_r^\circ$, HSV^c, HS^c, TSL, TS. Thus, out of $21*7 = 147$ investigated color spaces, only 22 has shown preliminary acceptable results. In this way, if a color space is selected by chance, there is only 15% hope that it will be helpful for OLUT–based skin detection. This fact proves that the ongoing investigation is worthy.

Another interesting outcome of the described experiment is the evaluation of the color spaces produced by altering elderly ones. There are six pairs of corresponding color spaces in this experiment. Namely, (HSI, HSI^c), (HSV, HSV^c), $(YC_bC_r, YC_bC_r^\circ)$, (YIQ, YIQ°), (YUV, YUV°), and $(IR_gB_y, IR_gB_y^+)$. As such, the comparison of the pairs of (HSI, HSI^c), (HSV, HSV^c), $(C_bC_r, C_bC_r^\circ)$, (IQ, IQ°), $(YUV.UV, UV^\circ)$, and $(R_gB_y, R_gB_y^+)$ shows that none of the manipulated color spaces outperform their regarding ancestors. In fact, the alterations in the structure of more classic color spaces have declined their performance.

An important result of this experiment is that in YUV, YIQ, and YC_bC_r, removing the illumination–related component (Y) increases the performance of skin detection. Thus, the definition of the illumination component in these three color spaces is a good step toward getting invariant to illumination.

Table I lists the resulting true and false positives of the best ROC curves obtained from the color spaces in this experiment. We believe that the difference between the performance of these color spaces is not meaningful. We emphasize that further comparison of these LUTs should be based on a larger dataset. Note that as the computation of the LUTs is performed using higher number of bins, there are some TP values less than the preselected margin of 90%. Here, we have used 32 and 256 bins for 3– and 2–D histograms, respectively, to acquire a more precise OLUT.

TABLE I

False and true positive results of the best LUTs produced by the color spaces under investigation.

Color Space	True Positive	False Positive
RGB	91%	5.9%
$HMMD$	90%	6%
$I_1I_2I_3$	91%	6.3%
HSI	85%	5%
HSV	93%	5.8%
C_bC_r	89%	7.9%
IQ	76%	3.1%
$YUV.UV$	90%	8.5%
$CIE-Luv$	91%	7.2%
Nbr	86%	8.7%
TSL	91%	6.4%

The skin map detection process is performed on the images in the erotic dataset, using each one of the 11 computed LUTs. Then, the results are separated into four categories of perfect, partial, excessive, and irrelevant. The perfect results are those, in which the skin detection process has carefully detected all skin pixels, with negligible false positives. The partial, and the excessive results are those with many false negative or many false positive pixels, respectively. Finally, irrelevant results are those in which the skin detection process has resulted completely unacceptably. Note that all these term are subjective definitions, and should be regarded carefully. Thus, the results of this test are only referable when there is a large difference between the portions of each category for two distinct LUTs. Figure 1–a shows the results. This tests reveals that the performance of Nbr is absolutely better than others. The reader should be aware that while Nbr gives the best possible OLUTs in this experiment, it has only performed perfectly in 49% of the erotic images. We argue that the weakness of the OLUT-based approaches comes from its essential definition that neglects the histogram of non–skin samples. This inefficiency is carefully considered in Baysian approach, discussed in Section III-C.

Selecting those color spaces capable of giving a BLUT satisfying $TP > 90\%$ and $FP < 20\%$, simultaneously, results in $CIE-a$, $CIE-u$, Min, $HSI.H$, R_g, R_g^+, C_r, C_r°, $YIQ.I$, Q°, $YUV.V$, and V°. Note that here we have doubled the margin for FP, as the ROC curves tend to fall in Baysian framework, compared to the OLUT–based one. Also, note that the ROC in $CIE-a$ is visibly outperforming others, even touching the $FP < 10\%$ margin. Note that selecting a color space by chance, there is only a 0.6% chance that it will yield proper BLUT–based skin detection results. Another interesting result of this experiment is that the best color spaces in Baysian framework are 1–D ones, compared to the case of OLUT–based skin detection in which the best eleven color spaces constitute eight 3–D, and three 2–D spaces and no 1–D color space.

There are six pairs of corresponding color spaces in this experiment. Namely, (HSI, HSI^c), (HSV, HSV^c), $(YC_bC_r, YC_bC_r^\circ)$, (YIQ, YIQ°), (YUV, YUV°), and $(IR_gB_y, IR_gB_y^+)$. The corresponding pairs of best combination of are $(HSI.H, H^c)$, $(HSV.S, H^c)$, (C_r, C_r°), $(YIQ.I, Q^\circ)$, $(YUV.V, UV^\circ)$, and (R_g, R_g^+). The experiment reveals that the HSI^c performs weaker compared to the HSI. In contrast, the HSV^c is far more better than the HSV. The $YC_bC_r^\circ$, YIQ°, and YUV° does not have anything to offer compared to their respective ancestors. IR_gR_y and $IR_gR_y^+$ are giving completely the same ROC curves.

Table II lists the resulting true and false positives of the best color spaces for BLUT–based skin detection. We again emphasize that further comparison of these BLUTs should be based on a larger dataset. Note that as the computation of the BLUTs is performed using higher number of bins, there are some TP values less than the preselected margin of 90%. Here, we have used 32 and 256 bins for 3– and 2–D histograms, respectively, to acquire a more precise BLUT. Note that the general results of BLUT–based skin detection are worse than those of OLUT–based skin detection in the training set.

TABLE II

FALSE AND TRUE POSITIVE RESULTS OF THE BEST BLUTS PRODUCED BY THE COLOR SPACES UNDER INVESTIGATION.

Color Space	True Positive	False Positive
Min	85%	13%
$HSI.H$	85%	13%
C_r	22%	93%
$CIE-a$	92%	14%
$YIQ.I$	83%	18%
$YUV.V$	89%	18%
$CIE-u$	57%	11%
R_g	78%	16%
R_g^+	74%	13%
V°	92%	28%
Q°	92%	28%
C_r°	95%	32%

The images in the erotic dataset are processed using the computed BLUTs. Then the results are separated into the four groups of perfect, partial, excessive, and irrelevant. Figure 1–b shows the results. It is clearly visible that V° and C_r° are dominantly outperforming the others. Comparing Figure 1–b with Figure 1–a reveals that utilizing the Baysian approach results in a higher rate of perfect classification, while it also increases the possibility of irrelevant vectors to be classified as skin. We argue that this occurs when both the nominator $(P(skin|\vec{c}))$ and denominator $(P(\sim skin|\vec{c}))$ of the fraction $p^+(\vec{c})$ get zero, resulting in an non–meaningful value. This fault may be resolved using a better control dataset (which includes more non–skin samples).

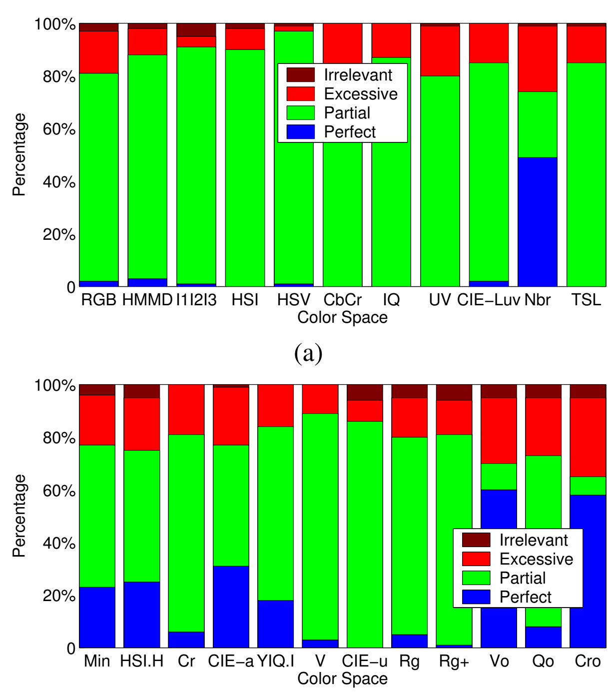

Fig. 1. Results of computing the skin map using the best available (a) LUTs. (b) BLUTs.

VI. Conclusions

Twenty–one different color spaces are examined for pixel–based skin detection. Each color space is considered in all seven possible representations. The examination included measuring the best performance for classifying the skin pixels in the training dataset plus the real performance in highlighting skin areas in the samples of a large pornographic dataset. Two approaches of ordinary and Baysian look–up table–based skin detection are evaluated here. The results shows that the Nbr is the best choice for ordinary look–up table–based skin detection. Also, it was observed that the best solutions for Baysian look–up table–based skin detection are 1–D color spaces of V° and C_r°. Utilizing the Baysian approach is proved to result in higher rate of perfect classification, while it also acceptably increases the possibility of false positives classification.

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