Comparison of pixel based skin recognition techniques

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Abstract: *Skin recognition has important role in image processing. Tasks like face detection, skin lesions, hand gesture analysis, image filtering relies on the performance of the skin recognition algorithm. In current paper are analyzed different approaches that are well known with the main goal to select the one with best results by testing medical images. Three categories of algorithms are selected for analysis: boundary model, parametric and non-parametric.*

Key words: *Skin, Color spaces , Bayes, Gaussian, Medical images.*

INTRODUCTION

Pixel based processing of images is one of the main approaches to segment human skin as it is relatively fast and simple to use. “Skin color” is not a physical property of an object it is rather a perceptual phenomenon and therefore a subjective human concept [8]. From implementation point of view three categories for modeling the skin are differentiated: explicitly defined skin regions, non-parametric, parametric.

The explicitly defined regions are probably the easiest and fastest way to recognize skin, since no hard computations are needed. They are based on usage of one or more color space representations and with threshold values skin pixels are differentiated. In a number of researches are given those best values.

Non-parametric skin distribution modeling estimates skin color distribution from the training data without deriving an explicit model of skin color and in contrast the parametric estimation derives parametric model.

COLOR SPACE

The color of skin in images depends primarily on the concentration of hemoglobin and melanin and on the conditions of illumination. It is well-known that the hue of skin is roughly invariant across different ethnic groups after the illuminant has been discounted. This is because differences in the concentration of pigments primarily affect the saturation of skin color, not the hue [2]. Most of the widely known algorithms like Bayes, Gaussian rely on range of defined color spaces. On the other hand boundary method might be used with much more color representations but the skin color detection significantly depends on the chosen color model, so here is provided a comparison between the most common color spaces used by researchers.

BOUNDARY METHOD WITH THRESHOLD VALUES

RGB is the most uncommon solution for skin recognition as this color space accuracy in varying illumination conditions is not distinctive. However this is the default format for images so no color space transformations are needed. This color is represented by its three channels R(red), G(green), B(blue). RGB is used in histogram detection technique as well, which is relatively fast and with good accuracy [2]. In RGB space are used threshold values introduced by Peer [7]. Because light has influence on the model two distinctive equations are jointed (for day and for night images) (1).

$$\begin{aligned}\big((R > 50)\,AND\,(G > 40)\,AND\,(B > 20)\,AND\,(\max(R,G,B) - \min(R,G,B) > 10)\,AND\,(R - G \\ \geq 10)\,AND\,(R > G)\,AND\,(R > B)\big)\ \mathbf{OR}\ \big((R > 220)\,AND\,(G > 210)\,AND\,(B \\ > 170)\,AND\,(R - G \leq 15)\,AND\,(R > B)\,AND\,(G > B)\big)\end{aligned} \tag{1}$$

Using **YCbCr** is possible to reduce the effect of different lightening conditions and skin color. This is result from the separated data for luminance and chrominance and human skin color model can be considered practically independent on the luminance and concentrated in a small region of the Cb-Cr plane. Transformation from RGB is linear and shown on (2). The threshold values (3) are proposed by many researchers [6,9] by a number of experiments. The values could be adjusted for more specific skin detection rules.

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \frac{1}{256}\begin{bmatrix} 65.738 & 129.057 & 25.064 \\ -37.945 & -74.494 & 112.439 \\ 112.439 & -94.154 & -18.285 \end{bmatrix}\begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad (2)$$

$$77 < Cb < 127, \qquad 133 < Cr < 173 \qquad (3)$$

HSV is also popular for skin detection. There is a lot variation of the standard as HSI, HSV/HSB, HSL(HLS) but basically the color is represented by three components: hue (H), saturation (S) and the brightness (I,V or L) [1]. Hue defines the dominant color (such as red, green, purple and yellow) saturation sets the colorfulness [8]. The main advantage of this color space is that data for hue and saturation could be extracted and the brightness to be dropped from the model and this would help in reducing the illumination dependencies. Essentially, HSV-type color spaces are deformations of the RGB color cube and they can be mapped from the RGB space via a nonlinear transformation and it is shown on (4).

$$Max = \max(R,G,B);\ min = \min(R,G,B);\quad delta = Max - min$$
$$H' = \begin{cases} undefined, & if\ delta = 0 \\ \frac{G-B}{delta} mod6, & if\ Max = R \\ \frac{B-R}{delta} + 2, & if\ Max = G \\ \frac{R-G}{C} + 4, & if\ Max = B \end{cases}$$
$$H = H' * 60^\circ;\ V = Max;\ S = \frac{delta}{V}, if\ delta \neq 0 \qquad (4)$$

The threshold values are given in (5) [4].

$$0 < H < 50, \qquad 0.23 < S < 0.68 \qquad (5)$$

CIELab is absolute color space. It is mathematically defined color space [1] that leads to separating the chromaticity from the brightness as well. It is based on extensive measurements of human visual perception, and serves as a foundation of many other colorimetric spaces. The nonlinear relations for L*, a*, and b* are intended to mimic the nonlinear response of the eye. As it is a uniform color space the Euclidean distance between two colors (defined as ΔE) is proportional to their visual difference. The three coordinates of CIELAB represent the lightness of the color (L* = 0 yields black and L* = 100 indicates diffuse white; specular white may be higher), its position between red/magenta and green (a*, negative values indicate green while positive values indicate magenta) and its position between yellow and blue (b*, negative values indicate blue and positive values indicate yellow). These values do not directly correspond to red, green, and blue, but are approximately so. The transformation is done in the following manner: first RGB is converted to XYZ (6) space and the XYZ is transformed to Lab as second step (7).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix}\begin{bmatrix} R \\ G \\ B \end{bmatrix} \qquad (6)$$

$$L^* = 116*\left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - 16, if\left(\frac{Y}{Y_n}\right) > 0,008856, \quad L* = 903.3*\left(\frac{Y}{Y_n}\right), if\left(\frac{Y}{Y_n}\right) \le 0,008856$$

$$a^* = 500\left[f\left(\frac{X}{X_n}\right) - \left(\frac{Y}{Y_n}\right)\right], \quad b^* = 200\left[f\left(\frac{Y}{Y_n}\right) - \left(\frac{Z}{Z_n}\right)\right] \qquad (7)$$

where $(t) = t^{\frac{1}{3}}, if\ t > 0,008856,\ f(t) = 7,787*t + \frac{16}{116} if\ t \le 0,0088$

X_n, Y_n, Z_n are reference values called white space and for the research are selected $[X_n, Y_n, Z_n] = [0.3127, 0.3290, 100$. For skin recognition might be used the Gaussian distribution with Euclidian distance [10] or simple threshold values (8) obtained after a number of experiments.

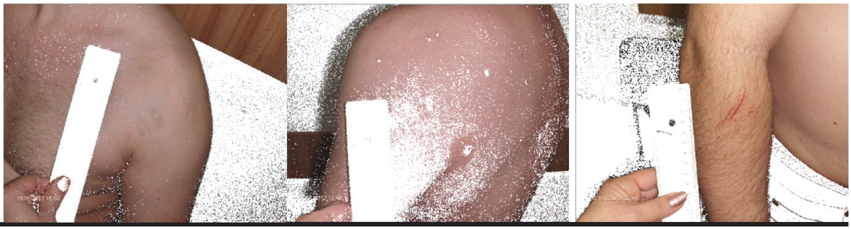
$$L^* > 35, \quad a^* > 1, \quad b^* > 1 \qquad (8)$$

HSCbCr is hybrid method that is used to obtain best results by combing results from YCbCr, HSV [7]. If both thresholds (3) (5) are satisfied the pixel is considered as skin.

The results from all mentioned color spaces in given in the table below.

Table 1. Results for boundary skin detection – first row contains the original images

HSV



NON PARAMETRIC METHODS

The algorithms in those methods does not derive explicit skin model and the advantages of this are basically two: they are fast in training and usage; they are theoretically independent to the shape of skin distribution (which is not true for explicit skin cluster definition and parametric skin modeling). The disadvantages are much storage space required and inability to interpolate or generalize the training data. If, for example, we consider RGB quantized to 8 bits per color, we'll need an array of 2^{24} elements to store skin probabilities [8]. In current system the data is kept in optimized way by storing just the channel info and in runtime all the 2^{24} possibilities are constructed.

For non-parametric algorithm is used the **Bayes** classifier with histogram technique proposed by John and Regh [2]. The Bayesian decision rule for minimum cost is a well-established technique in statistical pattern classification [5]. First the skin database is analyzed by gathering the manually segmented skin pixels and generating the skin histogram model and the non-skin histogram from the rest of the image pixels. The depth of the image is 2^{24} in RGB space or 256 colors per channel and the resulting histogram has divided the values in each channel by the count of each pixel in 256 bins for each channel. Currently the system is trained with 4000 images from the Compaq skin database [2]. The skin classifier is built from Bayes Maximum Likelihood (ML) that implies [5] (9).

$$\frac{P(rgb|skin)}{P(rgb|nonskin)} > \tau \qquad (9)$$

This means that pixel to be classified as skin its probability to be skin pixel should be greater by τ than the probability that this is non-skin pixel. The $P(rgb|sk$ is calculated by the formulas (10), $s[rgb]$ and $n[rgb]$ are the count for pixel in the skin and non-skin trained database and Ts and Tn are the total count of all pixels respectively. Results in Table 2 are obtained with $\tau = 0.4$.

$$P(rgb|skin) = \frac{s[rgb]}{Ts}, \qquad P(rgb|nonskin) = \frac{n[rgb]}{Tn} \qquad (10)$$

Table 2. Results from Bayes histogram technique: first row contains the original images, second the processed

PARAMETRIC METHODS

Lee [3] proposed new **Gaussian** distribution model called 'Elliptical boundary model' as alternative of Symmetric Gaussian model (SGM). The model is called elliptical as the skin pixels in chrominance space fits in an ellipse. The r-g chrominance model is used for current calculations because it could be obtained easily and the results and performance are good enough [3]. The chrominance represents the percentage of each color in the image regardless the luminance. c_i is the chrominance vector with dimension 2 as the third component is skipped, and n is the total number of distinctive vectors, N the total number of sample vectors, f_i is the count each c_i occurs in the training set, μ is the mean vector, Λ is the sample covariance matrix with 2x2 dimensions. The final result $\Phi(c)$ (11) gives the probability that c_i is skin pixel vector. Currently the threshold value is $\Phi(c) < 0.8$.

$$N = \sum_{i=1}^{n} f_i, \quad \mu = \sum_{i=1}^{n} f_i * c_i, \quad \varphi = \frac{1}{n} * \sum_{i=1}^{n} c_i, \quad \Lambda = \frac{1}{N} * \sum_{i=1}^{n} f_i * (c_i - \mu)(c_i - \mu)^T$$
$$\Phi(c) = (c_i - \varphi)^T * \Lambda^{-1} * (c_i - \varphi) \qquad (11)$$

Table 3. Results from elliptical boundary model: first row contains the original images, second the processed

CONCLUSIONS AND FUTURE WORK

Pixel based detection leads to many false positive results, even if using different color spaces (for example the wood material in background). The best performed color space is CIELab as it is leads to the smallest false positive detection percentage. With the Gaussian and Bayes classifier are obtained better results than simple boundary models. One assumption is that if the training data is specific for a case like medical images, false positive results might be reduced as the trained color model is specific as well. Future work aims implementation of texture analysis and pixel spatial dependent analysis and would rely on Gaussian distribution as best performed algorithm.

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The paper has been reviewed.