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COMPLEX COLOUR DETECTION METHODS USED IN SKIN DETECTION SYSTEMS

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In this paper we present high computational complexity algorithms for detecting skin and non-skin colour. Because of their complexity they are not suitable for nowadays mobile devices but can be used in systems working on more demanding machines. The selection and implementation of algorithms gives accuracy about 80-90%.

Keywords: face identification, authentication, biometrics, detection of skin colour

1. Introduction

Face detection is used in a wide variety of tasks related to the recognition of people, including authentication and identification systems. The approach of using facial biometric systems seems very natural due to the ease and non-invasive acquisition of sample face. Detection of skin colour is usually the first step of automatic face recognition [1, 2, 15]. To date there is a wide range of skin colour detection methods. From the application point of view these methods in identification systems can operate on mobile devices. But the computational complexity is a very important parameter.

Searching for skin colours can be used in different areas like face and gaze tracking [7, 8]. The skin has also its optics and there are some anthropological differences [5, 6].

In the previous paper, *Algorithms and methods used in skin and face detection suitable for mobile applications* [31] we presented algorithms and methods of image processing that can be used in image processing in mobile applications. Mobile applications can work on client side and can be used in mobile payment transactions i.e. using NFC.

In this section we would like to look at a more complex colour detection methods that can be used in systems identify the owner or user of the mobile device, where a portion of identification will be implemented at the application server side.

2. Parametric and nonparametric methods

The first of the algorithms that we want to analyze in the current paper is the one that identifies the colour in the images basing on standardization and classification of the RGB colour system and Bayesian classification, defined as:

$$P(skin|c) = \frac{P(c|skin)P(skin)}{P(c|skin)P(skin) + P(c|-skin)P(-skin)}$$

where *P (c | skin)* and *P (c |-skin*) skin and non-skin colours are taken from the histogram calculated by the following formula and normalization:

$$P_{skin}(c) = \frac{skin[c]}{Norm}$$

It gives a baseline for identifying skin. In order to further study the examples were used to train the histogram [11, 21, 22] and which has been illustrated by the following formula:

$$\frac{P(skin|c)}{P(-skin|c)} = \frac{P(c|skin)P(skin)}{P(c|-skin)P(-skin)}$$

where there was sought the difference between skin colour and the non-skin colour and these differences are described in the next formulas:

$$\frac{P(c|skin)}{P(c|-skin)} > \Theta, \quad \Theta = K \times \frac{1 - P(skin)}{P(skin)}$$

There was created a map on the basis of [16] that was designed to recognize only the skin and the non-skin using a database that you have been taught by manually tagged pictures of their recognition. The created database has been tested in [21] and other systems qualifications pixels. However, they were not obtained expected results.

Distribution of colours can be represented by modelling the joint density of probability functions:

$$P(c|skin) = \frac{1}{2\pi|\Sigma_s|^{1/2}} \cdot e^{-\frac{1}{2}(c-\mu_s)^T \Sigma_s^{-1}(c-\mu_s)}$$

where c means a colour vector, μ_s and Σ_s parameters and matrices. Subsequently there can be obtained from the following formulas:

$$\mu_s = \frac{1}{n}\sum_{j=1}^{n} c_j \qquad \Sigma_s = \frac{1}{n-1}\sum_{j=1}^{n}(c_j - \mu_s)(c_j - \mu_s)^T$$

where n is the total number of examples of colour and the probabilities of the skin is "measured" in c [28]. An alternative to the above calculation was the distance c from μ_s that created the matrix Σ_s [9]:

$$\lambda_s(c) = (c - \mu_s)^T \Sigma_s^{-1}(c - \mu_s)$$

Gaussian method was used in [13, 15, 27, 29]. Gaussian method based on identification of the skin in the case of the following formula p meant skin; the remaining values are the values p_i and standardization.

$$P(c|skin) = \sum_{i=1}^{k} \pi_i \cdot p_i(c|skin)$$

Distribution of the skin with specific histogram and Gaussian model turned out to be insufficient [26]. Elliptical boundaries were proposed in that model. It gave much better results in the database [21]. This was determined by the formula:

$$\Phi(c) = (c - \phi)^T \Lambda^{-1}(c - \phi)$$

where colour samples with low frequencies and minimal data are removed.

Then the coefficient ϕ is estimated by the formulas:

$$\phi = \frac{1}{n}\sum_{i=1}^{n} c_i \qquad \Lambda = \frac{1}{N}\sum_{i=1}^{n} f_i \cdot (c_i - \mu)(c_i - \mu)^T$$

$$\mu = \frac{1}{N}\sum_{i=1}^{n} f_i c_i \qquad N = \sum_{i=1}^{n} f_i$$

in which n is an integer specific to the colour of the skin. Vectors c training pixels and f_i is the number of samples of skin colours vector c.

An important advantage of this method is to determine the skin by simple rules of eligibility. But there is a problem how to determine the colour of the skin appropriately. There was used a learning machine, which has overcome mentioned problems [30]. However, time devoted to both machine learning and recognition of image elements is significant.

3. Method based on distance map of colours DM [17]

In this method there was declared SSC - the standard colour of the skin by the vector. Its length - n determines the colour and the C vector (C_1, C_2 ..... C_n). Defined colour length CD as Euclidean distance between colours and SSC. Mathematically represented by the formula:

$$\sqrt{\sum_{i=1}^{n} \left(C_i - C_{i_s}\right)^2} / Sp_{(C_1, C_2, \ldots, C_n)} \, .$$

For example, RGB it will be counted by the formula:

$$\sqrt{(R - R_s)^2 + (G - G_s)^2 + (B - B_s)^2} / Sp_{(R,G,B)}$$

and the last assumption that the DM is presented in gray scale determined by the pixel CD and convert to gray scale linearly recognized colours:

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

where $d(x, y)$ is the pixel distance in the system (x, y).

Through the above deductions generated RGB frame for your skin in daylight

$$R > 95, \quad G > 40, \quad B > 20$$
$$Max\{R, G, B\} - Min\{R, G, B\} > 15$$
$$|R - G| > 15, \quad R > G, \quad R > B$$

and in the sideway light

$$R > 220, \quad G > 210, \quad B > 170$$
$$|R - G| \leq 15, \quad B < R, \quad B > G$$

If both conditions are true gray scale is formed and then combined into a single DM and calculated using the following formula

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

where *x* and *y* represent the coordinates of pixels in the image. The following algorithm illustrates the action of successive steps how to obtain

```
Algorithm Find_SSC()[17]

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
Set μ = first significant local maximum in H
Set Th = first significant local minimum in H, where Th > μ.
If components of H in [μ, Th] is close to right half of Gaussian
then
If μ < ε then
       Return C.
       Else
       Set C = Median of colour of pixel whose CD is μ
       Generate a new DM, M, with respect to C as SSC
       Generate H of M
       Go to step 1.
End If
Else
H does not represent any skin region
End if
```

Below there is the algorithm searching in the image seeds of the skin and non-skin pixels.

```
Algorithm Find_Seed()

Input Parameters
M: The refined DM of the test image.
T_L: A low threshold.
T_H: A high threshold.

Procedure
If M(i,j) ≤ T_L then
The pixel at position (i,j) is a skin pixel.
Else If M(i,j) ≥ T_H then
The pixel at position (i,j) is non-skin pixel.
Else
The pixel at position (i,j) is an undefined pixel.
End If
```

At last the algorithm of growing the area of skins [18, 19, 20] is

```
Algorithm Region_Growing

Input Parameters
G: Gradient magnitude of DM
S: skin seed points

Output Parameters
Seg: Segmented image of the size same as G

       1.    Label each pixel in Seg as "skin", "non-skin" or
       "undefined" according to S and NS.
       2.    Add the neighbouring pixels of labelled region in the
       respective queues according to their gradient magnitude
       levels.
       3.    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 labelled neighbours, then it
             is labelled as them. Otherwise, it is labelled as a
             boundary pixel.
             c.    For each undefined neighbouring 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.
```

The method achieves excellent results and is able to find a light skin colour on the picture, regardless of the origin of the person shown on the picture, the background, lighting, and environments. It is effective for identifying areas without skin. In assessing effectiveness used, there was used Compaq database of the skin and non-skin. It includes an appropriate number of images of the skin and slow. 4000 randomly selected images containing areas of the skin and 5500 images slow to assess existing solutions. In addition to testing a randomly selected set of sequential images 500 consisting of 62,100,260 pixels, 9,859,733 pixels in the skin and 52,240,527 pixels slow. All the data obtained in Table 3 are the average values based on simulation 500 test images.

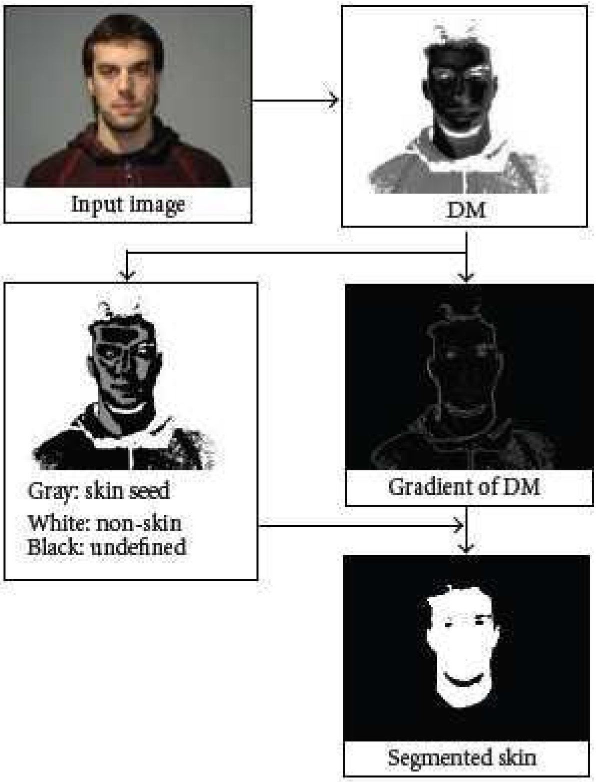

Figure 1. Algorithm workflow [17]

Table 1. Effectiveness of recognition methods of skin and non-skin colours [17]

Method / classifier	CDR (%)	FDR (%)	CR (%)
Traditional RGB method	81.2683	23.7099	77.0412
DM – described method	**89.9749**	**9.2695**	**90.6165**
Bayesian classifier [4, 14]	83.9234	10.9183	88.3034
Multilayer perceptron classifier [12]	83.3306	11.5401	87.6861
Colour consist with implementing neural networks [13]	85.6037	10.6809	88.7585
Segment- and edge-based refinements of Bayesian classifier [14]	82.6245	10.4442	88.4416
Principal feature analysis, PFA and Markov random field , MRF based methods [15]	83.9304	10.8703	88.3453

4. Pixel classification method [3]

Another algorithm is developed at the base of face detector [23] and the method of classification pixels [24]. With both elements it creates a map of the skin, not only for the type of Europeans but also for other anthropological types to form segments by the pixels and collects them in the LCH colour. This can be used in variety of methods i.e [10]. Using the method each pixel classification [24] is defined as the probability function of the skin:

$$P(skin|l,c,h) = Z\, e^{-\left(\frac{(l-\mu_l)^2}{2\sigma_l^2}+\frac{(c-\mu_c)^2}{2\sigma_c^2}+\frac{(h-\mu_h)^2}{2\sigma_h^2}\right)}$$

where *l, c, h* are the coordinates of the pixel map LCH, $\mu_l = 181$, $\mu_c = 32$, $\mu_h = 34$, $\sigma_l = 30$, $\sigma_c = 11$, $\sigma_h = 8$, and Z is a normalization factor. Probability of detection of the skin is compatible with a high factor, small, if it is low. The following are two methods for detecting the skin, wherein the first presupposes that the pixel is a skin:

$$w_x \frac{(x-\mu_x)^2}{2\sigma_x^2}, w_y \frac{(y-\mu_y)^2}{2\sigma_{yx}^2}, w_l \frac{(l-\mu_l)^2}{2\sigma_l^2}, w_c \frac{(c-\mu_c)^2}{2\sigma_c^2} \quad and \quad w_h \frac{(h-\mu_{xh})^2}{2\sigma_h^2}$$

Based on the weighted average over 1000 adjacent pixels in space of five functions. Where l, c, h means the position of the pixel in the x, y.

Another method assumes a Gaussian probability model in the space of five functions:

$$P(skin|l,c,h,x,y) = Z \cdot e^{-\left(w_l\frac{(l-\mu_l)^2}{2\sigma_l^2}+w_c\frac{(c-\mu_c)^2}{2\sigma_c^2}+w_h\frac{(h-\mu_h)^2}{2\sigma_h^2}\right)} \cdot e^{-\left(w_x\frac{(x-\mu_x)^2}{2\sigma_x^2}+w_y\frac{(y-\mu_y)^2}{2\sigma_y^2}\right)}$$

where Z is the normalization factor and the relative weight of each function. Then, to create a map of the skin, use the following function, which will give us a value indicative of the skin in the study area.

$$P(skin|c,h) = Z \cdot e^{-\left(w_c\frac{(c-\mu_c)^2}{2\sigma_c^2}+w_h\frac{(h-\mu_h)^2}{2\sigma_h^2}\right)}$$

The framework of the adaptation maps the colour is specified by the above formulas. They allow automatic segmentation of the skin pixels and then creating their prototype. Colour correction is performed using LAB colour areas, which represent the Cartesian cylindrical LCH

$$a = c \cdot \cos(h)$$
$$b = c \cdot \sin(h)$$

where *a* and *b* will be the prototype of skin in the plane of exposure CIECAM - UCS [25], *image a* and *image b* are the coordinates of computer memory and a_{orig} and b_{orig} are the coordinates of pixels. The variable *k* is the colour correction factor typically in the range of one.

$$a^*_{new} = a^*_{orig} + \Delta I_a kP\left(a^*_{orig}, b^*_{orig}\right)^\gamma$$
$$b^*_{new} = b^*_{orig} + \Delta I_b kP\left(a^*_{orig}, b^*_{orig}\right)^\gamma$$

At this level, the probability of a pixel is calculated skin. This algorithm, using information from the face detection and skin colour model and machine learning - learning model for every person of colour in the image and uses these models to calculate the maps of the skin. Each of the tested pixel is assigned probability of being skin.

The test consisted of two parts using outdoor images [3]. The first one was for training and algorithm tuning and contained 200 images from the Berkeley segmentation dataset [18], and was tagged by the authors [3]. The second one was used for testing and contained 196 images, and that was tagged by an external person. The results of the test are as follows:

- 80% of the skin pixels were tagged correctly,
- 21% was wrong detection.

5. Conclusion

In the previous paper, *Algorithms and methods used in skin and face detection suitable for mobile applications* [31] we presented image processing algorithms and methods of that can be used in authentication systems working on mobile client side. Their accuracy was about 80%. Their advantage was the low computational complexity and that is why they can be used in mobile applications.

Presented in this article, the skin colour detection methods generally provide better results in comparison with the methods being considered in the first part of the article. Their accuracy reaches 90% but their computational complexity is much higher than described in the paper mentioned above. These are methods can perform better in more complex situations where there are some disturbances that adversely affect the process of identifying the pixels representing the human skin.

In the case of skin colour detection algorithms in identification / authentication systems accuracy is about 80% and it may be insufficient. Therefore, there is a great demand for algorithms that provide greater accuracy of results. In this article, we presented a few selected methods that meet this criterion. These algorithms detect skin pixels in the image with the accuracy of about 90%. Such a result is generally satisfactory from the standpoint of further processing of subsequent image for the purpose of identification / authentication. Unfortunately, increasing the accuracy of these methods is associated with a fairly significant increase in computational complexity. These methods carry out a series of relatively complex mathematical transformations. Thanks these transformations we can extract additional information from the image.

The increase in computational complexity is so significant that it prevents us from using these solutions in applications running on the client side in currently available mobile systems/ devices. However, this does not mean, that they are completely unusable in our applications. Many identification / authentication systems allow us to perform some of the necessary calculations in this process on the server side. The server does not require such restrictive limitations on the computational complexity as for the algorithms running on mobile devices. Usually, the system has enough computing power to perform even the most complex calculations in real time. It seems that such a solution would also provide a very high quality of recognition and satisfactory operation time of the application. This assumption is based on the fact that the network connection has got sufficient bandwidth.

In addition, we expect that the computing power of mobile devices will continue to increase. Perhaps in the near future average commercially available mobile device will be able to cope with the complexity of the algorithms similar to those presented in the article.

In the case of authentication or identification systems the reliability of the result is so important that we should strive to use algorithms that give the highest accuracy, even at the expense of the significant increase in computational complexity.

From the presented tables it can be derived that the most promising results can be obtained from the methods using the distance map, DM. Therefore, it will be one of the methods used by us in further research on facial recognition systems operating on mobile devices using server-side processing.

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