Parametric Skin Distribution Modeling using Elliptical Boundary Model

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Abstract
Skin distribution in an image has been explored intensively for many years and becoming important part of computer-based human detection and recognition. Skin distribution can be modeled non-parametrically and parametrically. In this paper, a parametric method of skin distribution modeling named Elliptical Boundary Model (EBM) is presented. Experiment has been conducted in three chrominance color spaces using three group of face databases (FERET, SI and DWI). It is shown that EBM gives good detection.

Keywords: skin detection, skin color model, elliptical boundary model

1. Introduction

Exploration of skin detection in digital image has attracted many and various researchers in the world. Many papers have been published and presented in many journals and conferences. One of interesting and important elements of skin detection is how to model the skin distribution, therefore skin region in digital image can be located correctly and the result can be used for next intelligence applications.

This paper will present Elliptical Boundary Model to model the skin distribution parametrically. The EBM is used in the experiment of skin detection that detect skin-contain images that are collected from three database group, which are Face and Recognition Technology (FERET) database, Singular Inversions (SI) database, and Data Wajah Indonesia (DWI) database. All images in the experiment are represented in three chrominance color space, RGB, HSV and YCbCr.

2. Skin Modeling Overview

Literatures described that there are four approaches of skin modeling; those are direct approach, non parametric skin modeling, parametric skin modeling and dynamic skin distribution models. Direct approach determines explicitly the intensity values which are part of skin color. The determination process is computer based on several rules that are generated by performing experiments. Non parametric model describes a skin model by estimating the training data without explicitly define the model mathematically. A probability value of each pixel in image is assigned; this value will construct a Skin Probability Map (SPM) [7]. Normalized lookup table (LUT), Bayes classifier and Self Organizing Map (SOM) are non-parametric approaches. Parametric skin distribution generalizes and interpolates the training data. Therefore the model is more compact and representative, and independent from training data. Single Gaussian, Mixture Gaussian, Multiple Gaussian and Elliptical Boundary Model are considered as parametric techniques [6]. Dynamic skin distribution models combine all the approaches and usually implemented in tracking applications. Skin model can dynamically be adjusted automatically and adaptively based on the training images and other internal/external conditi

3. Histogram

Exploration of skin histogram has been performed using skin-selected region images using face averaging technique to show the histogram of skin pixels in RGB color space. The number of images that are
used for this exploration is 4012 images with various type, size and color bits. Statistical values are calculated and shown together with the histogram in the figure 1.

Skin in an image can also be presented in 2D or 3D representation. Figure 2 shows representation of the 3D skin distribution in three chrominance color spaces. Figure 3 shows a visualization of 2D skin distribution in three chrominance color space either.

By simply analyzing the histogram, we can obtain the preliminary fact that the skin region is located in specific area of an image. This feature can be used for performing more advance skin modeling, such as Elliptical Boundary Model.

<table>
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<th>FDB</th>
<th>Skin-only Image</th>
<th>R Component</th>
<th>G Component</th>
<th>B Component</th>
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<td><img src="image1" alt="Image" /></td>
<td><img src="hist1" alt="Hist" /></td>
<td><img src="hist2" alt="Hist" /></td>
<td><img src="hist3" alt="Hist" /></td>
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<td></td>
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<td>μ=104.28 δ=19.93</td>
<td>μ=71.02 δ=13.24</td>
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<tr>
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<td><img src="image2" alt="Image" /></td>
<td><img src="hist4" alt="Hist" /></td>
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<td>μ=95.74 δ=7.53</td>
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<td><img src="hist10" alt="Hist" /></td>
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<td></td>
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<td>μ=125.31 δ=16.30</td>
<td>μ=106.64 δ=14.72</td>
<td></td>
</tr>
</tbody>
</table>

Figure 1. Skin-only Image Histogram in RGB Color Space
3. **Elliptical Boundary Model**

First step of model approach is performed by generating Skin Distribution Map (SDM) [7] based on the three groups of face image models. We can show that the skin density is simple-shaped and the skin area in each chrominance space fits well an ellipse. This can be observed visually from Figure 3. With this observation, perform a statistical color model for skin detection, called an elliptical boundary model. This model is trained from a set of training data in two steps, preprocessing and parameter estimation. In preprocessing step we remove outliers so that the trained model reflects the main density of the underlying data set. In parameter estimation step we estimate model parameters from the preprocessed data set.

The detail explanation of the steps is described as follows:

1) **Training Face Data Set:**
In this step, face images from FERET, SI and DWI databases are collected and face region(s) are selected manually. The process selection can be done in multiple fashioned. The face-only images are saved and preprocessed.

2) Preprocessing Step:

In this step, noise and outliers are removed. Images that have extreme frequency intensities are also eliminated. These steps can be done by analyzing the histograms of the images.

3) Parameter Estimation:

In this step, estimation of ellipse is performed by examining the intensities of selected images using this ellipses boundary model.

\[ \Phi(X; \psi, \Lambda) = [X - \psi]^T \Lambda^{-1} [X - \psi] \]

Where \( X_i = X_1, \ldots, X_n \) is set of the distinctive chrominance vectors of the preprocessed training data set. While \( \psi = \frac{1}{n} \sum_{i=1}^{n} X_i \) and \( \Lambda = \frac{1}{n} \sum_{i=1}^{n} f_i (x_i - \mu)(x_i - \mu)^T \). Meanwhile \( N = \sum_{i=1}^{n} f_i \) is the total number of samples \( f(X_i) = f_i (i = 1, \ldots, n) \) in the preprocessed training data set and the vector \( \mu = \frac{1}{N} \sum_{i=1}^{n} f_i X_i \) is the mean of chrominance vectors.

\( X \) can be classified as skin if \( \Phi(X) < \Theta \) where \( \Theta \) is given threshold and \( X \) is input chrominance. The equality of \( \Phi(X) = \Theta \) defines the elliptical boundary model where \( \psi \) is the center of the ellipse and \( \Lambda \) is principal axes of the ellipse.

4. Experiment

Experiment has been conducted to prove the model in practice manner. Three databases are processed using the steps mentioned above. The sample of images that are used for this experiment can be seen in figure 4.
The result of the detection can be seen in the figure 5.

![Image of original image, preprocessing, ellipse parameter estimation, and cropping](image)

**Figure 5. Result of Skin Detection**

5. **Conclusion**

In this paper, a model that utilizes ellipse characteristics of skin distribution map has been presented and used for skin detection application successfully. The next step of this research is to check the model validity by using other images and shows them in ROC graph. This is to obtain the detection rate, including false detection and true detection rate.

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