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Skin Colour Detection Based on an Adaptive Multi-Thresholding Technique

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ABSTRACT

Skin colour is an important visual cue for face detection, face recognition, hand segmentation for gesture analysis and filtering of objectionable images. In this paper, the adaptive skin color detection model is proposed, based on two bivariate normal distribution models of the skin chromatic subspace, and on image segmentation using an automatic and adaptive multi-thresholding technique. Experimental results on images presenting a wide range of variations in lighting condition and background demonstrate the efficiency of the proposed skin-segmentation algorithm.

Keywords: Skin colour detection, adaptive multi-thresholding technique, skin-segmentation algorithm

INTRODUCTION

The skin colour detection algorithm is used as a post-processing step in order to separate skin regions from the background of a scene and treats the skin regions as candidate faces or hands for detecting and tracking. In pixel-based skin detection methods, the task can be considered as a standard two-class classification problem. This method will take each pixel of the input image and produce abinary output image ('1' represents skin pixel and '0' represents non-skin pixel). Pixel-based skin detection methods can be classified into three categories as shown in *Fig. 1* (Terrillon *et al.*, 2000; Vezhnevets and Andreeva, 2005; Vezhnevets *et al.*, 2003; Gomez and Morales, 2002; Lee and Yoo, 2002; Zarit *et al.*, 1999; Hsu *et al.*, 2002; Zhu *et al.*, 2004).

The parametric statistical approaches represent the skin-colour distribution in the parametric form, such as the Gaussian mode. A Gaussian distribution is a symmetrical frequency distribution having a precise mathematical formula relating the mean and standard deviation of the samples. The probability distribution function (PDF) used to describe the probability of the variant to belong to the group of data which have Gaussian distribution. A more sophisticated model, capable of describing complex-shaped distributions is the Mixture of Gaussians model (GMM) (Mukhopadhyay, 2000).

This work consists of two main steps. First, skin detection model Single Gaussia model (SGM) and GMM of the skin-color distribution are built based on sample pixels taken from a large number of people and in different lighting conditions. Second, skin-colour segmentation is performed based on the SGM and GMM of the skin-colour distribution, where an automatic adaptive thresholding technique is used to segment an image into skin and non-skin regions.

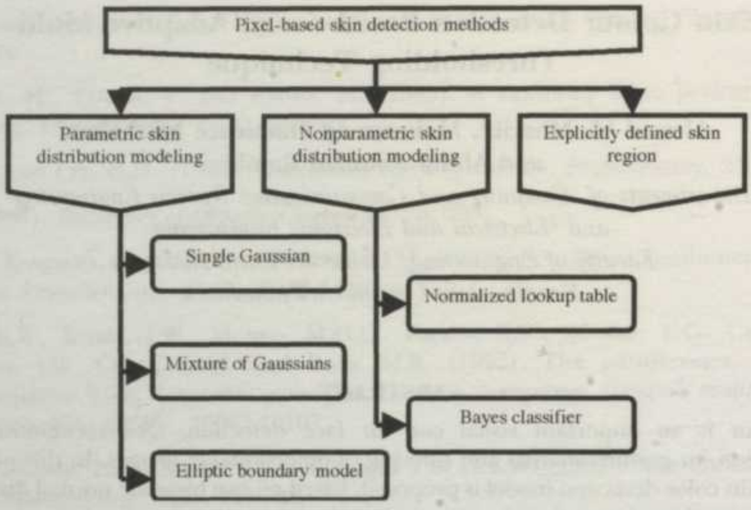

Fig. 1: Pixel-based skin detection methods

TRAINING DATA COLLECTION AND COLOR SPACE TRANSFORMATION

To cover a wide range of skin chromatic characteristics, 1000 skin samples (64×64 pixels) were used. These samples were extracted by using the Photoshop program from the JPEG image files collected from random sites, and from the different face database (7 face database). TSL (T is a tint value, S is a saturation value, L is a luminance value) colour space was chosen in this research. L component is eliminated to reduce the complexity of modeling the skin distribution into 2D model (Caetano and Barone, 2001). *Fig. 2* shows the 3D histogram distribution of the training data in TSL color space.

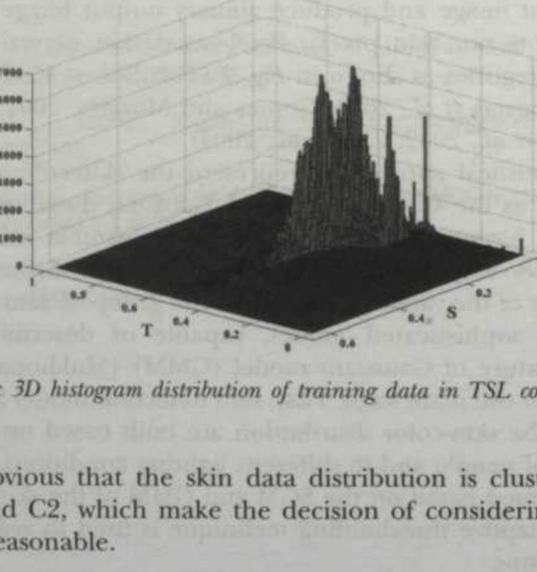

Fig. 2: 3D histogram distribution of training data in TSL color space

From *Fig. 2*, it is obvious that the skin data distribution is clustered into two groups referred to as C1 and C2, which make the decision of considering the GMM with two components more reasonable.

SGM AND GMM PARAMETERS ESTIMATION

The SGM parameters estimation was done by applying a simple mathematical operation on the collected training data as follows (Mukhopadhyay, 2000):

$$\mu_s = \frac{1}{N-1}\sum_{j=0}^{s-1} \mathrm{x}_j \tag{1}$$

$$\Sigma_s = \frac{1}{N-1}\sum_{j=1}^{N} (\mathrm{x}_j - \mu_s)(\mathrm{x}_j - \mu_s)^T \tag{2}$$

Where μ_s is the mean vector and $\sum_s$ is the covariance matrix, N is the total number of pixels and X is the color component of the training data.

GMM parameters estimation is more complicated than SGM. In this paper, the Expectation-Maximization algorithm is used for this purpose (Phung *et al.*, 2005). Two Gaussian components are used to represent the distribution of the skin colour in the GMM. The EM algorithm is run on the training data until the difference between the consecutive likehood-function values is an accepted small value.

THE SKIN DETECTION MODEL

The proposed skin detection model (SDM) is constructed based on the SGM and the GMM. Each one of them detects the skin pixels of a still image separately, then an OR logical operation is applied on the skin map images. Thus any pixel that will be detected as skin by any one of these two models will be considered as skin pixel. The estimated parameters values of SGM and the two Gaussian components of the GMM (C1 and C2) are substituted in the PDF. The following expressions introduce the used skin detector model in this paper (Gokalp, 2005).

$$P(T,S|\Theta) = \frac{a}{2\pi\sigma_T\sigma_S\sqrt{1-\rho^2}} \times e^{\frac{-1}{2(1-\rho^2)}\times\frac{(T-\mu_T)^2}{\sigma_T^2} - \frac{2\rho(T-\mu_T)(S-\mu_S)}{\sigma_T \times \sigma_S} + \frac{(S-\mu_S)^2}{\sigma_S^2}} \tag{3}$$

$$\rho = \frac{\sigma_{TS}}{\sigma_T . \sigma_S} \tag{4}$$

$$P(T,S|\Theta)_{GMM} = P(T,S|\Theta)_{C1} + P(T,S|\Theta)_{C2} \tag{5}$$

Where T and S represent the Tint value and Saturation value in TSL color space of the tested pixel respectively, (μ_T, σ_T) and (μ_s, σ_S) represent the training data mean and standard deviation of Tint and Saturation respectively, σ_{TS} represent the training data covariance of Tint and Saturation and represent the probability of each pixel to be classified as a skin. The probability maps of SGM and the GMM are shown in *Fig. 3*.

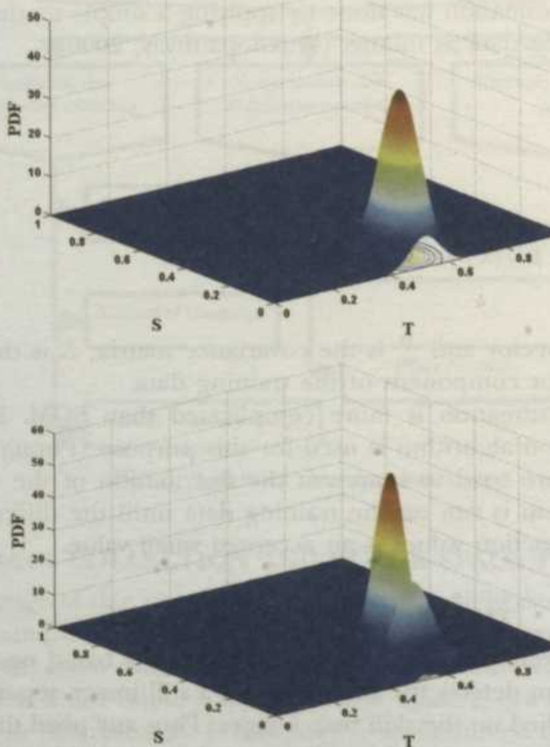

Fig. 3: The probability map of skin color distribution (a: SGM and b: GMM)

THE OPTIMAL THRESHOLD VALUE ESTIMATION

An automatic and adaptive multi-thresholding estimation technique is used to obtain the optimal threshold values of the SGM and the GMM. The following procedures illustrate how these values are estimated:

1. Each pixel in the input test image will be applied in the PDF of the SGM and GMM.
2. Pixels with the probability less than 0.1 will be neglected.
3. The average of the pixel's probabilities (greater than 0.1) will be calculated for the SGM and the GMM (APSG and APGM).
4. $(thr)_{SGM} = F_{GM} \times APSG$ and $(thr)_{SGM} = APSG$. Where F_{SGM} is the threshold factor of SGM, and F_{GMM} is the threshold factor of GMM.

F_{SGM} and F_{GMM} will be estimated graphically. *Figs. 4* and *5* show different behaviours for almost all the relationships between the threshold factor values and the error rate of SGM and GMM respectively, for test example images. The evaluation of the error rate is considered both for the non-skin pixels classified as skin and real skin pixels classified as the non-skin. The following expression explains this:

$$ER = \left(\frac{SCN}{number\ of\ real\ skin\ pixels} + \frac{NCS}{number\ of\ non\ skin\ pixels}\right) \times 100 \tag{6}$$

Where SCN is the number of the real skin pixels in the test image which has been classified as non-skin; and NCS is the number of the non-skin pixels which have been classified as skin.

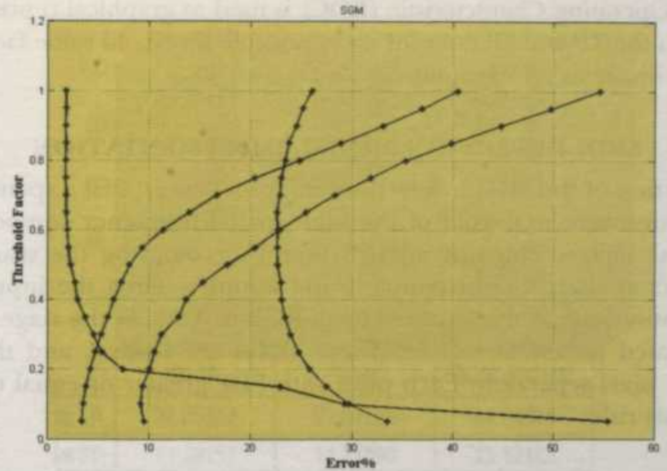

Fig. 4: Examples of the relationship between the threshold factor values and the error rate in SGM

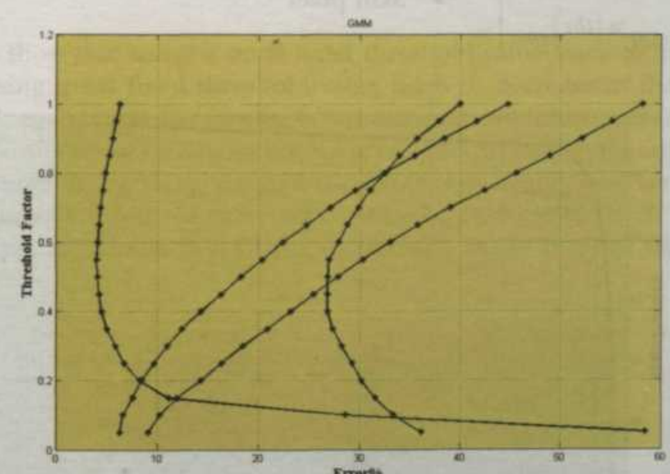

Fig. 5: Examples of the relationship between the threshold factor values and the error rate in GMM

The threshold value factors should be chosen in the range where the error is minimum. Unfortunately, some test images have the minimum error rate when the threshold factor is a small value, and others have it when the threshold factor is a bigger value. In this case, appropriate values should be used for all possible conditions. From *Figs. 4* and *5*, it can be observed that the threshold values of the SGM and GMM in the range from 0.2 to 0.4 represent a suitable choice.

THRESHOLD VALUE FACTOR

The threshold value factor plays an important part in the skin detection process. The results show that by decreasing F_{SGM} and F_{GMM}, The True Positive (TP) and The False Positive (FP) increased, and by increasing F_{SGM} and F_{GMM}, TP and FP decreased. In this paper, Receiver Operating Characteristic (ROC) is used as graphical representation of the trade off between the TP and FP rates for every possible threshold value factor. *Fig. 6* shows a ROC of a test image as an example.

SKIN DETECTION MODEL IMPLEMENTATION

The implementation of the SDM involved several procedures, first a spatial low pass filter is used with input image to devoid of the high spatial frequency components that may be present in the image. This operation is useful in removing the visual noise, which generally appears as sharp bright points in the samples. Then the input image colour space representation will be transformed from RGB to TSL. At the stage of applying the SDM, the estimated parameters of SGM and GMM are loaded, and the SDM will be applied on each pixel separately. Each pixel with PDF greater or equal to the threshold value will use this rule:

$$\left.\begin{matrix} P(T,S|\Theta)_{SGM} \geq (thr)_{SGM} \\ OR \\ P(T,S|\Theta)_{GMM} \geq (thr)_{GMM} \end{matrix}\right\} \rightarrow \text{Skin pixel} \quad (7)$$

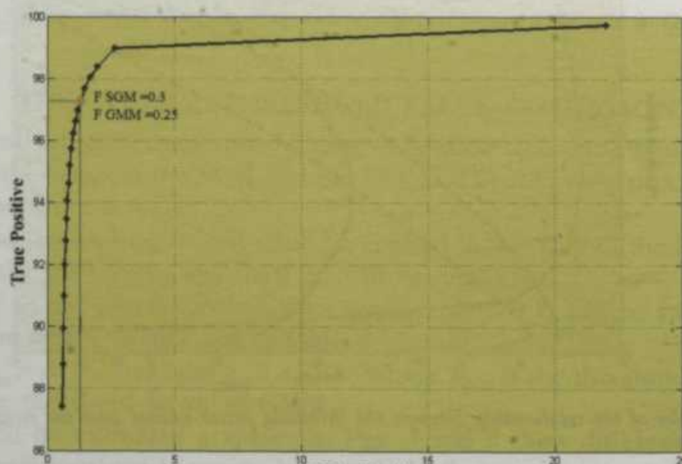

Fig. 6: The ROC of testing image 1

EXPERIMENTAL RESULTS

To test the performance of the proposed method, 45 test images of people from various ethnic groups under various conditions are used. The model performance can be evaluated as how the TP value can be greater and how the FP value can be smaller at the same time. Experiment results show that, when SGM and GMM are used together, TP value is always greater than TP value in the model based on SGM or GMM being used separately. When SGM and GMM are used together, FP is almost equal to the greater value of FP of SGM or GMM. *Fig. 7* illustrates this observation.

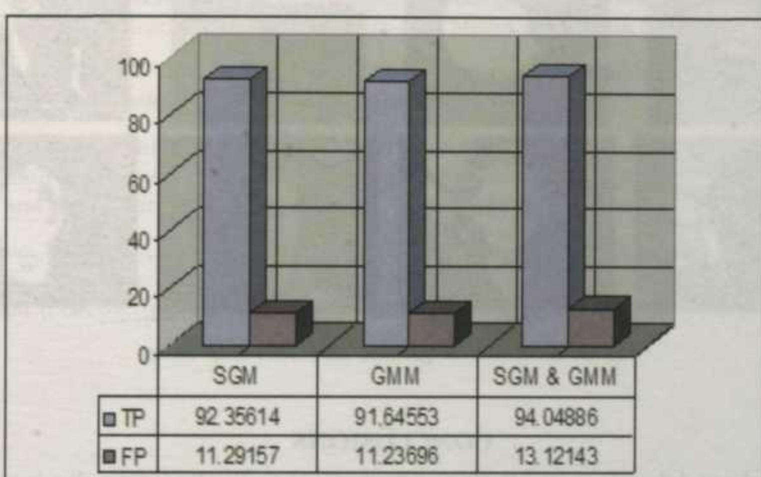

Fig. 7: Model performance comparisons: SGM, GMM and SGM and GMM

The results show that using a small fixed threshold value leads to increase in the TP and FP, and using great fixed threshold value leads to decrease in the TP and FP. On the other hand, each image has its own environmental conditions such as ambient lights, complex backgrounds and others, where some images can be segmented to skin and non-skin regions perfectly by using a small threshold value, and vice versa. For all these reasons, the adaptive threshold value represents the solution for such problems. *Fig. 8* shows a performance comparison of the model with three kinds of threshold values.

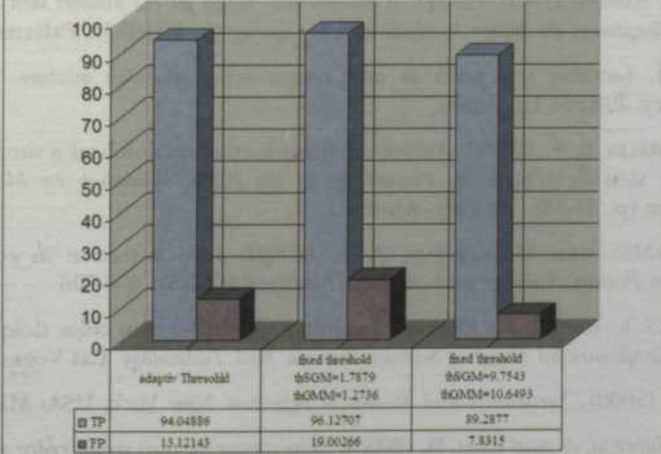

Fig. 8: Model performances with three kinds of threshold values

Fig. 9 shows some test images and their skin map images.

Fig. 9: Some test images and their skin map image

CONCLUSIONS

The suggested model shows an efficiency performance in detecting the human skin in still colour images, apart from the variety of the human races and the complexity of the backgrounds. The SDM performs normally when the image contains shadowed skin, but not to the same degree of accuracy when images contain human skin under bright light conditions. The experimental results show that the average of the accuracy rate of the test images as more than 94%, while the standard deviation is 4.2%.

However, there are several problems with the proposed SDM method. These problems include when the background contains surfaces and objects with skin-like colours. In such cases, the results show that the TP value can be accepted as usual, where the results also show that in such images, the FP rises to 50% and more.

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