

Skin Colour Segmentation using Fintte Bivariate Pearsonian Type-IV a Mixture Model

K.SRINIVASA RAO
Department of Statistics, Andhra University, Visakhapatnam-03
ksraoau@yahoo.co.in

B.N.JAGADESH
Department of CSE, Srinivasa Institute of Engineering & Technology, Cheyyeru, Amalapuram
nagajagadesh@gmail.com

CH.SATYANARAYANA
Department of CSE, JNTUK, Kakinada
chsatyanarayana@yahoo.com

Abstract
The human computer interaction with respect to skin colour is an important area of research due to its ready applications in several areas like face recognition, surveillance, image retrievals, identification, gesture analysis, human tracking etc. For efficient skin colour segmentation statistical modeling is a prime desiderata. In general skin colour segment is done based on Gaussian mixture model. Due to the limitations on GMM like symmetric and mesokurtic nature the accuracy of the skin colour segmentation is affected. To improve the accuracy of the skin colour segmentation system, In this paper the skin colour is modeled by a finite bivariate Pearsonian type-IVa mixture distribution under HSI colour space of the image. The model parameters are estimated by EM algorithm. Using the Bayesian frame the segmentation algorithm is proposed. Through experimentation it is observed that the proposed skin colour segmentation algorithm perform better with respect to the segmentation quality metrics like PRI, GCE and VOI. The ROC curves plotted for the system also revealed that the developed algorithm segment pixels in the image more efficiently.
Keywords: Skin colour segmentation, HSI colour space, Bivariate Pearson type IVa mixture model, Image segmentation metrics.

1. Introduction

Colour is an important factor that can be used to detect and classify the objects in an image. For efficient utilization of the automatic detection systems of human it is required to study and analyze algorithms for skin colour segmentation in images [1, 2]. Skin detection is widely used in image processing applications like Face tracking, Gesture Analysis, Face detection, Content Based Image Retrievals, Medical Diagnostics and several other human computer interaction domains. Much work has been reported in literature regarding skin colour modeling and detection. Kakumanu et al [3] have reviewed the literature on skin colour modeling and detection methods, they also mentioned that the choice of colour space is an important factor for skin colour classification. J. Yang et al [4] have observed that skin colour differ more in intensity rather than chrominance.

Several colour spaces have been used for skin colour segmentation. The basic color spaces like RGB, Normalized RGB, and CIE-XYZ are used by [5, 6, 7, 8, 9]. The perceptual colour space like HSI, HSV, HSL and TSL are used by [10, 11, 12, 13, 9, 14]. Orthogonal colour space namely YCbCr, YIQ, YUV, YES etc are used by [15, 16, 17, 18, 19, 20]. Other colour spaces like CIE – Lab, CIE – Luv are used by [21, 7, 22]. Among all these colour spaces the HSI offers the advantage that separate channels outline certain colour properties and the visual conjunctive system of human being is close to the features of the colour pixels are characterized by intensity, hue and saturation[23]. Rafel C et al [24] has stated the HSI is ideal for digital image processing since it is closely related to the way in which people describe the perception of colour. Therefore in this paper we consider the feature vector associated with the skin colour of the image pixel is characterized by a bivariate random vector consists of hue and saturation. The HSI colour space hue and saturation are functions of intensity (I), we consider only the hue and saturation values to reduce complexity of computation and to avoid redundancy with out loosing information of the image.

The authors [4, 8, 25, 3, 26, 27] have developed skin colour segmentation methods based on probability distributions since model based segmentation is efficient than other methods of segmentation. In most of the colour segmentation it is customary to consider single Gaussian model or Gaussian mixture model for characterization the skin colours. Recently to overcome the drawback associated with colour object tracking using Gaussian mixture model, Ketchantang et al [28], have developed Pearson based mixture model for colour object tracking. He used the results based on pixel intensity values under univariate consideration. Very little work has been reported regarding skin colour segmentation utilizing bivariate Pearson type-1Va mixture model under HSI colour space. The Pearson type-IVa mixture model includes a wide variety of bivariate distributions that have Gamma family of marginal distributions.

It is empirically observed that the hue and saturation of a pixel in a colour image are skewed and having positive range. Another advantage of the Pearson type-IVa distribution is having only two parameters. It is well known that if the number of parameters is less then the model gives over efficient characterization of the physical phenomenon. Hence, in this paper a colour image segmentation algorithm is developed and analyzed assuming that the feature vector consisting of hue and saturation values of the image follows a two component mixture of bivariate Pearson type-IVa distribution.

Rest of the paper is organized as follows. Section 2 deals with two component bivariate Pearsonian type-IVa mixture model and its properties which are used for modeling the skin colour. Section 3 deals with estimation of model parameters using EM Algorithm. It is observed that the Expectation Maximization algorithm gives efficient estimators in mixture models. Section 4 is concerned with the initialization of model parameters using K-means algorithm. The K-means algorithm is used to divide the colour image pixels in to two categories, initially for obtaining the initial estimators of the model parameters. Section 5 presents the skin colour segmentation algorithm based on maximum likelihood under Bayesian frame. The Experimental results along with the performance of the proposed algorithm are given in section.6. Section 7 deals with the conclusions.

2. Bivariate Pearson TYPE-IVa Mixture Model

In skin colour analysis the classification of the image is done into two categories namely, skin and non-skin colour regions. The skin colour is different from the colour of most other natural objects in the world. To build the statistical model for the pixels in the image, the feature vector is extracted using colour spaces. In skin colour segmentation one has to use the chrominance component in extracting the features. Accordingly the hue and saturation under HSI colour space are used for skin colour detection. The statistical observations of hue and saturation which form a bivariate feature vector match closely with the bivariate Pearson type-IVa distributions. The bivariate Pearson type-IVa given by [29] is having non negative and asymmetric nature of the random variable. It also includes a wide variety of bivariate probability distributions. Here it is assumed that the feature vector of the pixel in skin or non-skin regions in the image follows a bivariate Pearson type-IVa

$$f(x,y/\theta)=\frac{x^{m-1}(y-x)^{n-1}e^{-y}}{\Gamma(m)\Gamma(n)} \qquad \begin{matrix} m,n>0 \\ 0<x<y \end{matrix} \tag{1}$$

θ is the parametric set such that $\theta=(m,n)$, x denote the hue value and y denote the saturation value of the pixel in the image.

The marginal probability density function of the hue value is

$$f(x)=\frac{x^{m-1}e^{-x}}{\Gamma(m)} \qquad m>0 \tag{2}$$

Its mean is m and variance is m

The marginal probability density distribution of the saturation value is

$$f(y)=\frac{(y-x)^{n-1}e^{-(y-x)}}{\Gamma(n)} \qquad n>0 \tag{3}$$

Its mean is $n+m$ and variance is $n+m$

The Covariance between hue and saturation values is m

Since the entire image is a collection of skin and non-skin pixel regions which are characterized by a bivariate Pearson type-IVa distribution, The feature vector associated with the whole image is modeled as a two component bivariate Pearson type-IVa mixture model. Its Joint probability density function is

$$h(x,y)=\sum_{i=1}^{2}\alpha_i f_i(x,y/\theta_i) \tag{4}$$

where, $0<\alpha_i<1$ and $\alpha_1+\alpha_2=1$ and $f_i(x,y)$ is as given equation (1).

3. ESTIMATION OF THE MODEL PARAMETERS USING EM-ALGORITHM

The likelihood function of bivariate observations $(x_{1,}y_1),(x_{2,}y_2),(x_{3,}y_3),\ldots,(x_{N,}y_N)$ drawn from an image with probability density function $h(x,y;\theta)=\sum_{i=1}^{K}\alpha_i f_i(x_s,y_s;\theta\ )$ is

$$L(\theta)=\prod_{s=1}^{N}(\sum_{i=1}^{K}\alpha_i f_i(x_s,y_s;\theta\ ))$$

$$=\prod_{s=1}^{N}(\sum_{i=1}^{K}\alpha_i \frac{x^{m-1}(y-x)^{n-1}e^{-y}}{\Gamma(m)\Gamma(n)})\ m,n>0 \tag{5}$$

This implies

$$\log L(\theta)=\log\prod_{s=1}^{N}(\sum_{i=1}^{K}\alpha_i f_i(x_s,y_s;\theta\ ))$$

$$=\sum_{s=1}^{N}\log(\sum_{i=1}^{K}\alpha_i f_i(x_s,y_s;\theta)) \tag{6}$$

The model parameters are estimated by using the Expectation Maximization Algorithm (E.M Algorithm).

The updated equation of the parameter α_k is

$$\alpha_k^{(l+1)}=\frac{1}{N}\sum_{s=1}^{N}[t_k(x_{s,}y_s;\theta^{(l)})] \qquad \text{for K = 1, 2.}$$

$$=\frac{1}{N}\sum_{s=1}^{N}\left[\frac{\alpha_k^{\ l}f_k(x_{s,}y_s;\theta^{(l)})}{\sum_{i=1}^{2}\alpha_i^{\ l}f_i(x_{s,}y_s;\theta^{(l)})}\right] \tag{7}$$

where, $f_k(x_{s,}y_s;\theta^{(l)})$ is as given equation (1).

The updated equation of m_k at $(l+1)^{th}$ iteration is

$$\sum_{s=1}^{N} t_k(x_s, y_s; \theta^{(l)}) \log(x_s) - \sum_{s=1}^{N} t_k(x_s, y_s; \theta^{(l)}) \frac{1}{\Gamma m_k} (\Gamma m * \log(\log(e)) - \Gamma m * Psi(m) * \log(e^{-m}) = 0 \quad (8)$$

where Psi (m) = digamma (m)

The updated equation of n_k at $(l+1)^{th}$ iteration is

$$\sum_{s=1}^{N} t_k(x_s, y_s; \theta^{(l)}) \log(y_s - x_s) - \sum_{s=1}^{N} t_k(x_s, y_s; \theta^{(l)}) \frac{1}{\Gamma n_k} (\Gamma n * \log(\log(e)) - \Gamma n * Psi(n) * \log(e^{-n}) = 0 \quad (9)$$

where Psi (n) = digamma (n)

Solving the equations (7), (8) and (9) iteratively using MATLAB code we get the revised estimates of α_k, m_k, n_k for K = 1, 2.

4. INITILIZATION OF MODEL PARAMETERS BY K-MEANS

The efficiency of the EM algorithm in estimating the parameters is heavily dependent on the initial estimates of the parameters. The number of mixture components taken for K-means algorithm is two (skin and non-skin), i.e., K = 2. Usually the mixing parameter and the region parameters (m, n) are unknown. A commonly used method in initialization is by drawing a random sample in the entire image data [30, 31]. This method perform well only when the sample size is large, and the computation time is heavily increased. When the sample size is small it is likely that some small regions may not be sampled. To overcome this problem, we use K-means algorithm [32] to divide the whole image into two homogeneous regions representing skin and non-skin regions. We obtain the initial estimates of the parameters m and n for each image region using the method of moment estimators for bivariate Pearson type-IVa distribution and for the parameters α_i as $\alpha_i = \frac{1}{2}$ for i = 1, 2.
Therefore the initial estimates of m and n are:

$m_k = \overline{x_k}$ is the k^{th} region sample mean of the Hue value

$n_k = \overline{y_k}$ is the k^{th} region sample mean of the Saturation value.

Substituting these values as the initial estimates, we obtain the refined estimates of the parameters by using the EM-Algorithm.

5. Skin Colour Segmentation Algorithm

After refining the parameters the prime step is skin colour segmentation, by allocating the pixels to the skin or non-skin segments. This operation is performed by segmentation algorithm. The skin colour segmentation algorithm consists of the following steps

Step 1) Divide the whole image into two regions using K-means algorithm

Step 2) Obtain the initial estimates of the model parameters using the moment estimators as discussed in section 4 for each region

Step 3) Obtain the refined estimates of the model parameters by using the EM-algorithm with the updated equations given in section 3.

Step 4) Substitute the estimated parameter values in the image joint probability density function

$$h(x, y) = \sum_{i=1}^{K} \alpha_i f_i(x, y; \theta_i) \quad \text{where} \quad f_i(x, y / \theta_i) \text{ is as given equation (1).}$$

Step 5) Segment the pixels as skin colour or non-skin colour pixel using a threshold (t) and the likelihood function such that $L(x/\theta) \geq t$ or $L(x/\theta) < t$ respectively for 0 < t < 1.

The optimal threshold value of t is determined by computing true positive and false positive over the segmented regions and plotting the ROC Curve.

6. Experimental Results and Performance Evaluation

In this section, the performance of the developed skin colour segmentation algorithm is evaluated. For this purpose the skin images are collected from JNTUK database and UCD colour face database. A random sample of 5 images is taken from both the databases and the feature vector consists of hue and saturation for each pixel of the each image is computed utilizing HSI colour space. In HSI colour space the hue and saturation values are computed from the values of RGB for each pixel in the image using the formula

$$\text{Hue} = \text{H} = \cos^{-1}\left[\frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}}\right], B \leq G$$

$$= 2\prod - \cos^{-1}\left[\frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}}\right], B > G$$

$$\text{Saturation} = \text{S} = \frac{1-\min(R,G,B)}{I}$$

where $I = \frac{R+G+B}{3}$ is the intensity of pixel.

With the feature vector (H, S) each image is modeled by using the two component bivariate Pearson type-IVa mixture distribution. The initial values of the model parameters are obtained by dividing all the pixels in to two categories namely skin and non-skin region using K-means algorithm with K = 2 and taking and moment estimates for (m, n), I =1, 2. Using these initial estimates and the updated equations of the EM-algorithm discussed in section.3 with MATLAB code the refined estimates of model parameters are obtained. Substituting the refined estimates in the bivariate Pearson type –IVa the joint probability distribution functions of the skin colour and non-skin colour models of each image are estimated. The segmentation algorithm with component maximum likelihood under Bayesian frame and a threshold value t as discussed in section 5 is used to segment the image. Figure 1 shows the original and segmented random images.

The developed algorithm performance is evaluated by comparing skin colour segmentation algorithm with the Gaussian mixture model. Table.1 presents the miss classification rate of the skin pixels of the sample image using proposed model and Gaussian mixture model.

From the Table.1, it is observed that the misclassification rate of the classifier with bivariate Pearson type-IVa mixture model (BPTIVaMM) is less compared to that of GMM. The accuracy of the classifier is also studied for the sample images by using confusion matrix for skin and non-skin regions. Table .2, shows the values of TPR, FPR, Precision, Recall and F-measure for skin and non-skin segments of the sample images.

From Table.2, it is obtained that the F-measure value for the proposed classifier is more. This indicates the proposed classifier perform better than that of Gaussian mixture model. Figure.2 shows the ROC curves associated with the proposed skin colour classifier and the classifier with GMM.

From the Figure.2 it is observed that the proposed classifier is having less false detection of the skin pixels compared to the classifier with GMM. The figure also shows that can successfully identified the exposed skin region including face, hands and neck.

The performance of the segmentation algorithm is also studied by obtaining three segmentation performance measures namely, Probabilistic Rand Index (PRI) [33], Variation of Information (VOI) [34], Global

Consistency Error (GCE) [35] with the sample images. The computed values of the performance measures for the developed algorithm with BPTIVaMM and GMM are presented in Table. 3.

From the Table.3 it is observed the PRI value of the proposed algorithm for sample images considered for experimentation are more than that of the value from the segmented algorithm based on GMM and they are closed to 1. Similarly the GCE and VOI values of the proposed algorithm are less than that of finite Gaussian mixture model and closed to 0. This reveals that the proposed segmentation algorithm performs better than the algorithm with GMM and the skin colour segmentation is closed to the ground truth.

7. Conclusion

In this paper we have proposed a skin colour segmentation by modeling the colour image pixels through two component bivariate Pearson type-IVa mixture model under HSI colour space. The bivariate Pearson type-IVa is a capable of characterizing the skin colour having only two parameters. The less number of parameters gives a good fit to the image data. This mixture model also includes different styles of bivariate distributions. The model parameters are estimated by EM algorithm. The initialization of parameters is done through K-means algorithm and moment method of estimation. The experimentation with five different types of images have revealed that the proposed segmentation algorithm perform better with respect to image segmentation metrics like PRI, VOI and GCE. The ROC curves plot for the images using the proposed method and the method based on Gaussian mixture model shows that the proposed algorithm can be further refined by considering unsupervised skin color segmentation with more number of classes for background, skin colour, non human objects, etc. It is also possible to utilize the Hidden Markov Model with bivaraiate Pearson type-IVa mixture model which will be taken elsewhere.

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Figure 1. Original and Segmented images

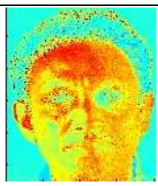
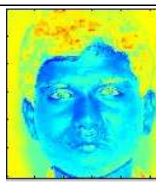
Images	Image 1 (Female1)	Image 2 (Male1)	Image 3 (Female2)	Image 4 (Male2)	Image 5 (Male3)
Original					
Segmented					

Table.1 Miss Classification rate of the classifier

Model	Miss Classification Rate
BPTIVaMM	8%
GMM	14%

Table.2 Comparative study of GMM and BPTIVaMM

Image	Method	TPR	FPR	Precision	Recall	F-measure
Image1 (Female1)	BPTIVaMM	0.9421	0.1020	0.9545	0.9421	0.9280
	GMM	0.8972	0.1820	0.9090	0.8972	0.9030
Image2 (Male1)	BPTIVaMM	0.8968	0.092	0.9096	0.8968	0.9031
	GMM	0.8648	0.1153	0.8771	0.8648	0.8709
Image3 (Female2)	BPTIVaMM	0.9191	0.075	0.9220	0.9191	0.9205
	GMM	0.8240	0.158	0.8538	0.8240	0.8380
Image4 (Male2)	BPTIVaMM	0.9042	0.1010	0.9082	0.9042	0.9061
	GMM	0.8419	0.1230	0.8729	0.8419	0.8571
Image 5 (Male3)	BPTIVaMM	0.9210	0.0740	0.9284	0.9210	0.9246
	GMM	0.8873	0.1185	0.8972	0.8873	0.8922

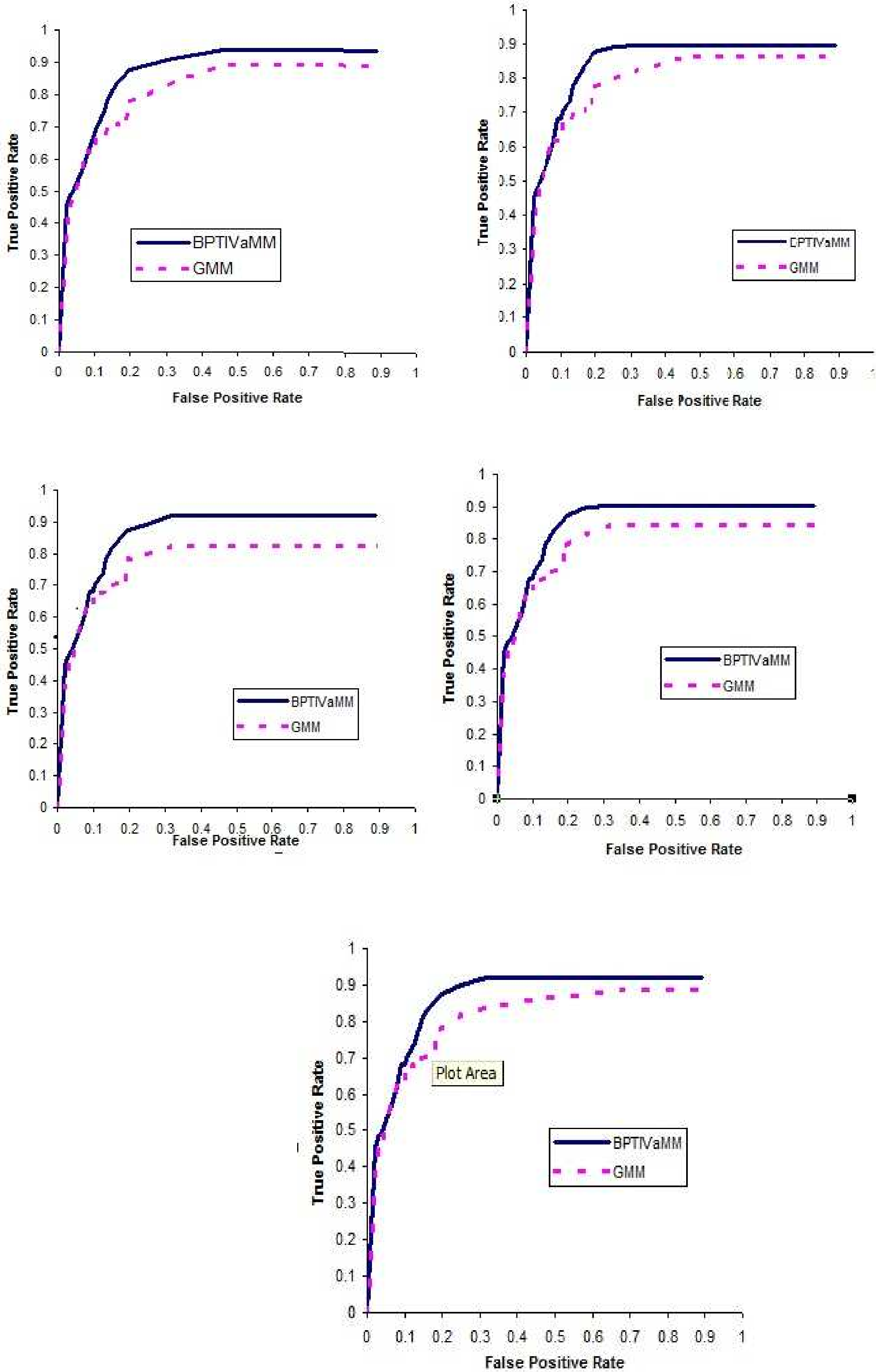


Figure. 2 ROC Curves

Table 3.Segmentation Performance Measures

Image	Method	Performance Measures		
		PRI	GCE	VOI
Image 1 (Female1)	BPTIVaMM	0.5823	0.2824	0.1240
	GMM	0.4526	0.3268	0.1860
Image 2 (Male1)	BPTIVaMM	0.7218	0.2215	0.0921
	GMM	0.4438	0.3820	0.1282
Image 3 (Female2)	BPTIVaMM	0.5246	0.1864	0,1248
	GMM	0.3983	0.2962	0.1861
Image 4 (Female3)	BPTIVaMM	0.7824	0.1986	0.1326
	GMM	0.6982	0.2859	0.2025
Image 5 (Male2)	BPTIVaMM	0.6368	0.2504	0.0762
	GMM	0.5610	0.3294	0.2362