A BIVARIATE PEARSON TYPE-II $a\alpha$ MIXTURE MODEL BASED SKIN COLOUR SEGMENTATION USING HIERARCHICAL CLUSTERING

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***Abstract*—**Model based segmentation plays an important role in many segmentation algorithms. Modeling the skin colour of face recognition is one of the challenging task in image analysis. Hence in this paper, a new skin colour segmentation algorithm is proposed based on bivariate Pearson type-II $a\alpha$ mixture model with hierarchical clustering algorithm. The model parameters are estimated using EM algorithms. Through experimentation the proposed skin colour segmentation algorithm performs better with respect to PRI,VOI and GCE.

Keywords*—*Skin Colour, Pearson type-II $a\alpha$ mixture model, Hierarchical Clustering, Face Recogntion.

I. INTRODUCTION

Skin colour segmentation plays an important role in many applications such as face detection, face tracking, gesture analysis, human computer interaction, computer vision etc. Skin colour can also be used as complementary information to other features and can be used to build accurate face detection system. The feature for the detection of skin region is by skin colour, so that the colour space plays a dominant role for feature extraction. Colour space is a multi dimensional space where different components of colours are being represented with different dimensions. Several colour spaces have been used for skin colour segmentation[1-6]. 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 which are characterized by intensity, hue and saturation[7-9]. Therefore in this paper, the feature vector associated with the skin colour of the image pixel which is characterized by a bivariate random vector and it consists of hue and saturation.

Recently much work has been reported in literature regarding skin colour segmentation by various authors [10-12] and the model based segmentation methods are more efficient than other methods since they capture the local and global information of the images more effectively [13]. In model based skin colour segmentation it is customary to assume that the feature vector associated with the colour image is either Gaussian or Gaussian mixture model. But the Gaussian or Gaussian mixture model have certain drawbacks like the feature vector in each region are meso-kurtic and having infinite range. In reality the feature vector in each region of the image (skin and non-skin regions) may not be meso-kurtic and more so having finite range. To overcome this drawback in colour image segmentation based on Gaussian mixture model it is developed and analyzed the skin colour segmentation algorithm with the assumption that the feature vector (consists of hue and saturation of the skin or non-skin regions) follows a bivariate Pearson type-II $a\alpha$ mixture models. The bivariate Pearson type-II $a\alpha$ mixture models are more versatile distributions and includes different shapes of the frequency curves associated with asymmetric/lepti/ platikurtic distributions.

The rest of the paper is organized as follows: section 2 given brief discussion about bivariate Pearson type-II $a\alpha$ mixture model and its properties. Section 3 deals with the estimation of the model parameters using EM Algorithm. Section 4 is to initialize the model parameters using Hierarchical clustering algorithm. In Section 5 the skin colour segmentation algorithm is presented based on likelihood function under Bayesian frame work. In section 6 the experimentation and performance evaluation of the proposed algorithm are discussed. Section 7 deals with conclusion.

II. BIVARIATE PERASON TYPE–II $a\alpha$ MIXTURE MODEL

The statistical observations of hue and saturation form a bivariate feature vector match closely with the bivariate Pearson type-II $a\alpha$ distributions. The bivariate Pearson type-II $a\alpha$ given by Samuel Kotz et al. (2000)[14] 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-II $a\alpha$ distribution. The Joint probability density function of the feature vector is

$$f(x,y/\theta)=\frac{\Gamma(m+n+p)}{\Gamma(m)\Gamma(n)\Gamma(p)}x^{m-1}y^{n-1}(1-x-y)^{p-1}$$
$$m,n,p>0 \qquad (1)$$
$$x,y>0\ and\ x+y\le 1$$

θ is the parametric set such that $\theta=(m,n,p)$, x denote the hue value and y denote the saturation value of the pixel in the image. The various shapes of the bivariate frequency surfaces of Pearson type-II $a\alpha$ mixture model are shown in Figure 1

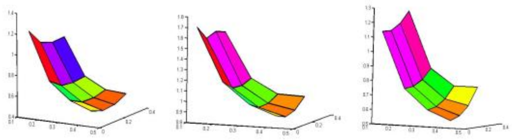


Figure 1. shapes of bivariate Pearson type-II $a\alpha$ model frequency surfaces

Its Joint probability density function is

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

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

III. ESTIMATION OF THE MODEL PARAMETERS USING EM-ALGORITHM

In this section, the estimates of the model parameters through Expectation-Maximization (EM) algorithm. The likelihood function of bivariate observations $(x_1,y_1),(x_2,y_2),(x_3,y_3),...,(x_N,y_N)$ drawn from an image with probability density function

$$h(x,y;\theta)=\sum_{i=1}^{2}\alpha_i f_i(x_s,y_s;\theta)$$
$$L(\theta)=\prod_{s=1}^{N}h(x_s,y_s;\theta)$$
$$=\prod_{s=1}^{N}\left(\sum_{i=1}^{2}\alpha_i f_i(x_s,y_s;\theta)\right)$$

This implies

$$\log L(\theta)=\sum_{s=1}^{N}\log\left[\sum_{i=1}^{2}\alpha_i\frac{\Gamma(m+n+p)}{\Gamma(m)\Gamma(n)\Gamma(p)}x^{m-1}y^{n-1}(1-x-y)^{p-1}\right] \qquad (3)$$

The updated estimate of α_k after $(l+1)^{th}$ iteration is

$$\alpha_k^{(l+1)}=\frac{1}{N}\sum_{s=1}^{N}[t_k(x_s,y_s;\theta^{(l)})]$$
$$=\frac{1}{N}\sum_{s=1}^{N}\left[\frac{\alpha_k^{(l)}f_k(x_s,y_s;\theta^{(l)})}{\sum_{i=1}^{k}\alpha_i^{(l)}f_i(x_s,y_s;\theta^{(l)})}\right] \qquad (4)$$

where,

$$f(x,y)=\frac{\Gamma(m+n+p)}{\Gamma(m)\Gamma(n)\Gamma(p)}x^{m-1}y^{n-1}(1-x-y)^{p-1}$$

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

$$\sum_{S=1}^{N}t_k(x_s,y_s;\theta^{(l)})\log(x_s)+\sum_{S=1}^{N}t_k(x_s,y_s;\theta^{(l)})$$
$$\psi(m_k+n_k+p_k)-\sum_{S=1}^{N}t_k(x_s,y_s;\theta^{(l)})\psi(m_k)=0$$

where, $\psi(m_k)$ = digamma (m_k)

and $\psi(m_k+n_k+p_k)$=digamma$(m_k+n_k+p_k)$ (5)

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

$$\sum_{S=1}^{N}t_k(x_s,y_s;\theta^{(l)})\log(y_s)+\sum_{S=1}^{N}t_k(x_s,y_s;\theta^{(l)})$$
$$\psi(m_k+n_k+p_k)-\sum_{S=1}^{N}t_k(x_s,y_s;\theta^{(l)})\psi(n_k)=0$$

where, $\psi(n_k)$ = digamma (n_k)

and $\psi(m_k+n_k+p_k)$=digamma$(m_k+n_k+p_k)$ (6)

The updated estimate of p_k after $(l+1)^{th}$ iteration is

$$\sum_{S=1}^{N}t_k(x_s,y_s;\theta^{(l)})\log(1-x_s-y_s)+\sum_{S=1}^{N}t_k(x_s,y_s;\theta^{(l)})$$
$$\psi(m_k+n_k+p_k)-\sum_{S=1}^{N}t_k(x_s,y_s;\theta^{(l)})\psi(p_k)=0$$

where, $\psi(p_k)$ = digamma (p_k)

and $\psi(m_k+n_k+p_k)$=digamma$(m_k+n_k+p_k)$ (7)

Solving equations (4), (5), (6) and (7) iteratively using MATLAB code we get the revised estimates of $\alpha_k, m_k, n_k\ and\ p_k$ for k=1, 2.

IV. INITILIZATION OF MODEL PARAMETERS USING HIERARCHICAL CLUSTERING

In this section, the methods of obtaining initial estimates of the model parameters to run the EM algorithm. The likelihood function contains two components. The pixels of the whole image are initially divided into two groups namely skin and non-skin regions by using Hierarchical clustering algorithm. In this method to initialize the parameter α_k and the model parameters $m_k, n_k\ and\ p_k$ is Hierarchical Clustering[15]. The initial values of α_i can be take n as $\frac{1}{2}$ i.e., $\alpha_i=\frac{1}{2}$, for i = 1, 2. The Average Linkage algorithm [16] is used by defining the distance between two segments to be the average distance between a point in one segment and a point in the other segment. The proximity between the new segment, denoted (r, s) and old segment (k) is defined in this way.

$$d_{(r,s)K} = \frac{\sum_i \sum_j d(i,j)}{N_{(r,s)} N_k}$$

where d (i, j) is the distance between object i in the cluster (r, s) and object j in the cluster k and N_k is the number of items in the k^{th} region. The above procedure is repeated fill the distance between two clusters is less than the specified threshold value.

After obtaining the final value of the number of regions k, we obtain the initial estimates of $\alpha_{k,} m_{k,} r_k$ for the k^{th} region using segmented region values with moment method of estimation for bivariate Pearson type-II $a\alpha$ mixture model with initial parameters. After getting this initial estimates for $\alpha_{k,} m_{k,} r_k$, we obtain the final refined estimates of the parameter through EM – algorithm.

V. 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 algorithm is described as follows

1. Divide the whole image into two regions using Hierarchical clustering algorithm.
2. Obtain the initial estimates of the model parameters using the moment estimators as discussed in section 4 for each region
3. Obtain the refined estimates of the model parameters by using the EM-algorithm with the updated equations given in section 3.
4. Substitute the estimated parameter values in the image joint probability density function

$$h(x,y) = \sum_{i=1}^{2} \alpha_i f_i(x,y\ ;\theta_i) \quad \text{where}$$

$f_i(x, y/\theta_i)$ is as given equation (1).

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 computing true positive and false positive over the segmented regions and plotting the ROC Curve.

VI. EXPERIMENTATION 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 Indian database. A random sample of three images is taken from the database and the feature vector consists of hue and saturation for each pixel of the each image is computed utilizing HSI colour space. The feature vector (H, S) each image is modeled by using the two component bivariate Pearson type-II $a\alpha$ mixture distribution. The initial values of the model parameters $\alpha_1, \alpha_2, m_1, m_2, n_1, n_2, p_1\ and\ p_2$ are obtained by dividing all the pixels into two categories namely skin and non-skin regions using Hierarchical clustering algorithm with k = 2, and taking $\alpha_1 = \alpha_2 = \frac{1}{2}$ and moment estimates for $(m_i, n_i\ and\ p_i)$, 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 and presented in tables 1, 2 and 3.

Table 1
Estimated values of the parameters for Female1 image, Number of image regions (k=2)

Parameters	Estimated Initial Parameters by Hierarchical clustering		Estimated Final Parameters by EM-Algorithm	
	Regions(i)		Regions(i)	
	1	2	1	2
α_i	0.5	0.5	0.2128	0.7872
m_i	0.0670	0.4662	0.2418	0.7940
n_i	0.2580	0.0802	0.1080	0.0178
p_i	0.1625	0.2732	0.1749	0.4059

Table 2
Estimated values of the parameters for Male1 image, Number of image regions (k=2)

Parameters	Estimated Initial Parameters by Hierarchical clustering		Estimated Final Parameters by EM-Algorithm	
	Regions(i)		Regions(i)	
	1	2	1	2
α_i	0.5	0.5	0.5280	0.4720
m_i	0.2010	0.0750	0.0392	0.8281
n_i	0.0782	0.4323	0.3122	0.1820
p_i	0.1396	0.2536	0.1757	0.5050

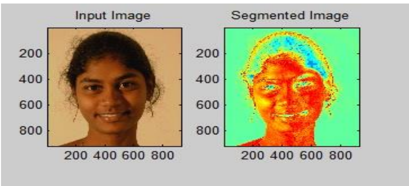
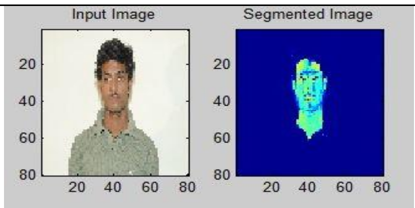
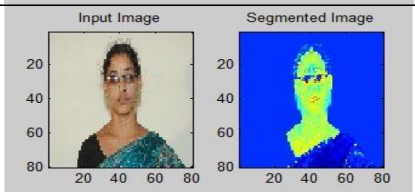
Table 3
Estimated values of the parameters for Female2 image, Number of image regions (k=2)

Parameters	Estimated Initial Parameters by Hierarchical clustering		Estimated Final Parameters by EM-Algorithm	
	Regions(i)		Regions(i)	
	1	2	1	2
α_i	0.5	0.5	0.3715	0.6285
m_i	0.1524	0.1040	0.0042	0.9965
n_i	0.5887	0.0386	0.2192	0.2549
p_i	0.3705	0.0713	0.1117	0.6257

Substituting the refined estimates in the bivariate Pearson type-II $\alpha\alpha$ joint probability distribution function 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. Figures.2 shows the original and segmented images.

Figure 2 Original and Segmented Images

Image Name	**Original and Segmented Image**
Female 1	
Male 1	
Female 2	

The developed algorithm performance is evaluated by comparing skin colour segmentation algorithm with the BGMM with K-Means and BPTII $\alpha\alpha$ MM with K-means. Table 4 present the misclassification rate of the skin pixels of the sample image using proposed model, BGMM with K-Means and BPTII $\alpha\alpha$ MM with K-means.

Table 4
MISCLASSIFICATION RATE OF THE CLASSIFIER

Model	Misclassification Rate
BGMM with K-means	11.2%
BPTII $\alpha\alpha$ MM with K-means	8.2%
BPTII $\alpha\alpha$ MM with Hierarchical	7.6%

From Table 4, it is observed that the misclassification rate of the classifier with bivariate Pearson type-II $\alpha\alpha$ mixture model (BPTII $\alpha\alpha$ MM) with hierarchical clustering is less compared to that of BGMM with K-Means and BPTII $\alpha\alpha$ MM with K-means. The accuracy of the classifier is also studied for the sample images by using confusion matrix for skin and non-skin regions. Table 5 shows the values of TPR, FPR, Precision, Recall and F-measure for skin and non-skin segments of the sample images.

From Table 5, it is obtained that the F-measure value for the proposed classifier is more. This indicates the proposed classifier perform better than that of BGMM with K-Means and BPTII $\alpha\alpha$ MM with K-means.

Table 5
COMPARATIVE STUDY OF EXISTING AND PROPOSED METHODS

Image	Method	TPR	FPR	Precision	Recall	F-measure
Image1 (Female1)	BGMM with K-means	0.9285	0.1875	0.9454	0.9285	0.9368
	BPTII $\alpha\alpha$ MM with K-means	0.9642	0.0625	0.9818	0.9642	0.9729
	BPTII $\alpha\alpha$ MM with Hierarchical	0.9708	0.0416	0.9789	0.9708	0.9748
Image2 (Male1)	BGMM with K-means	0.9166	0.0833	0.9565	0.9166	0.9363
	BPTII $\alpha\alpha$ MM with K-means	0.9625	0.0181	0.9788	0.9625	0.9705
	BPTII $\alpha\alpha$ MM with Hierarchical	0.9729	0.0458	0.9769	0.9729	0.9748
Image3 (Female2)	BGMM with K-means	0.9307	0.1120	0.9518	0.9307	0.9411
	BPTII $\alpha\alpha$ MM with K-means	0.9692	0.0629	0.9767	0.9692	0.9729
	BPTII $\alpha\alpha$ MM with Hierarchical	0.9750	0.0416	0.9790	0.9750	0.9784

The performance of the segmentation algorithm is also studied by obtaining three segmentation performance measures namely, Probabilistic Rand Index (PRI), Unnikrishnan.R et al (2007), Variation of Information (VOI), Meila M. (2005), Global Consistency Error (GCE), Martin D.et al (2001) with the sample images. The computed values of the performance measures for the developed algorithm with BGMM with K-Means and BPTII $\alpha\alpha$ MM with K-means are presented in Table. 6.

Table 6
SEGMENTATION PERFORMANCE MEASURES

Image	Method	Performance Measures		
		PRI	GCE	VOI
Image 1 (Female1)	BGMM with K-means	0.5128	0.2486	0.1529
	BPTII $a\alpha$ MM with K-means	0.6941	0.1928	0.0892
	BPTII $a\alpha$ MM with Hierarchical	0.7452	0.1429	0.0816
Image 2 (Male1)	BGMM with K-means	0.5367	0.2249	0.0981
	BPTII $a\alpha$ MM with K-means	0.7810	0.2016	0.0716
	BPTII $a\alpha$ MM with Hierarchical	0.8218	0.1826	0.0649
Image 3 (Female2)	BGMM with K-means	0.4826	0.1924	0.1626
	BPTII $a\alpha$ MM with K-means	0.6721	0.1281	0.0926
	BPTII $a\alpha$ MM with Hierarchical	0.7625	0.0938	0.0728

From Table.6, 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 BGMM with K-Means and BPTII $a\alpha$ MM with K-means and they are close to 1. Similarly the GCE and VOI values of the proposed algorithm are less than that of finite BGMM with K-Means and BPTII $a\alpha$ MM with K-means and close to 0. This reveals that the proposed segmentation algorithm performs better than the algorithms with BGMM with K-Means and BPTII $a\alpha$ MM with K-means and the skin colour segmentation is close to the ground truth.

VII CONCLUSION:

A novel skin colour segmentation based on bivariate Pearson type-II $a\alpha$ mixture model with hierarchical clustering algorithm is presented. In this approach the pixels of the skin and non-skin regions in the image are characterized by hue and saturation values. The bivariate Pearson type-II $a\alpha$ distribution used for skin region and it is capable of identifying the skin regions more effectively since it consider the non-negative nature of the feature vector and correlation between hue and saturation values in the colour space. The model parameters are estimated by deriving the updated equation of the EM-Algorithm for the bivariate Pearson type-II $a\alpha$ mixture model. Experimentation is carried with three images randomly selected from the JNTUK database having skin and non-skin regions. A comparative study of the performance measures like the misclassification rate, Precession, Sensitivity and F-ratio for the proposed method and the segmentation with BGMM with K-Means and BPTII $a\alpha$ MM with K-means and it reveals that the proposed method perform better in skin colour identification. The segmentation performance measures of the image like PRI, VOI and GCE shown that the proposed method segments the image more close to the ground truth.

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