Novel Segmentation Algorithm based on Mixture of Multiple Histograms

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Abstract

In any man machine interaction system, a fast and accurate skin color classification is a challenging step, and the detection of skin color considered as the preliminary step in various recent applications such as face detection and gesture recognition. Segmentation based skin color process should be robust, accurate, and feasible for specific application field. Color distribution modeling techniques varies in its simplicity and complication according to particular color space and modeling technique parameters. Histogram technique has proven its outstanding capability of skin color classifications. In this work we adopted a novel method for hand gesture classification based on the mixture of histogram with look up table LUT applied on several three color models are combined into single model by assigning weight for each histogram based color model separately. The suggested system mechanism inspired from Hasan and Mishra [25] but they utilized Gaussian mixture model rather than the histogram technique. the performance of the proposed system evaluated using two methods in order to examine system efficiency comparing with other skin color classification systems including system performed by [25], these methods are; classification rate CR and accuracy. System results revealed that our system outperforms over other systems in term of accuracy and classification rate by achieving 99.48% and 98.9349 respectively.

Keywords: Skin Color, segmentation, histogram, lookup table (LUT), GMM, color space, RGB, YCbCr, HSV.

1. Introduction

In colored images, the detection of skin color considered the most essential step in many applications such as face and hand detection and tracking [1], video surveillance [2]. In order to achieve reliable [1] system a lot of researches tried to combine an extra cues [1][3] and features with the available skin color information such as intensity and range data [4], or depth information and temperature acquired from stereo camera and thermal camera respectively [5] or with the object shape [1] and motion feature [6].

With the evolution and widely diffusion of the colored cameras/ video cameras, the skin color became the most powerful cue utilized for human face and hand detection [1].

A lot of techniques have been applied for modeling the human skin color distribution pixels by taking the advantages that they are dealing with the color feature which provide simple, fast and size invariant [1] facilities, however, the problems appear with any slightly varying in ambient illumination [1].

The popular statistical modeling techniques for skin detection utilized is histogram [7][8], single Gaussian model [9][10], mixture of Gaussian model [11][2]. The histogram modeling technique represent the most simple and fast method [9][10] but requires largely adequate data for effective result performance [9]. Single Gaussian model technique is more general [9] and Fast but under variant lightness changes, the variance of the color distribution area [9], the remedy for this problem is to apply mixture of Gaussian model which can model each clustering distribution area separately, although it can model complex data distribution [9], but it is computational consuming in parameters initialization, estimation, and evaluation [9].

This paper is organized as follows: section 2 explained color distribution modeling techniques, Section 3 shows the framework of skin color detection with demonstrating of each of the color model conversions, modeling technique utilized and proposed system layout. The related works are discussed in Section 4, and system performance evaluation metric is explained in Section 5. Section 6 showed the experimental results, and finally conclusion in Section 7.

2. Color Distributions Modeling Techniques

Pixel based color distribution modeling techniques provide an instrument for differentiating skin and non-skin pixels in specific area [12][13]. Different studies have been introduced in the literature for color modeling, and shape modeling [10][14] where the latter modeling require discriminate between background and object of interest [14], these techniques comprise: explicitly defined skin region, Statistical skin distribution modeling techniques.

Explicitly defined skin region technique: also named *generic skin model* [15] a fixed predefined range is defined to construct this modeling technique by separating the boundaries of the skin area in the suitable chosen color space [10] [13]. The input image is classified into either an object or background by examining image pixels successively [16]. The training data are used to extract the prefect range for classifying [10]. This method is very common for fast and simple skin color segmentation purposes since no training phase are needed [12], however, it this technique is restricted and quite affected with lighting changes [10], and not accurate in skin detection [1]. Thresholding techniques represent an example of this technique.

Statistical color modeling: these techniques used training data for modeling the distribution of the skin color; these methods can be further subdivided into:

i) Non-parametric Color Distribution Modeling

The skin color probability is estimated from the available training data and hence there is no need for an explicit modeling method for fitting the data [12][10][13]. These methods are robust [17], fast in implementing and not affected with the skin distribution shape [13], however, they are storage space consumption [13], unable to generalize the training data [13], and weak against illumination changes [17]. An example of these techniques is Histogram with Bayesian classifier are used to classify the skin pixels using conditional probability [10][12], Normalized lookup table (LUT) [13] and, Self Organizing Map (SOM) [13].

ii) Parametric Color Distribution Modeling

In this modeling system, the pixels are classified into skin and non-skin pixels by building a statistical model that capable of approximating the trained data [10]. This modeling technique can generalize small size the trained data [18] and represent complex data distribution shape [13], which is represented in a parametric statistical form [10], however, the initialization and estimation of the model parameters usually performed using some statistical iteration algorithms such as k-means clustering and Expectation Maximization that provides an initialization and estimation of the model parameters respectively [10][13]. The advantages of these methods that they depends hardly on the data distribution shape and require small storage space [13] but they are training and running slowly and require computations . Single Gaussian and mixture Gaussian model are examples on these modeling techniques.

3. Skin Color Detection Framework

For any skin color detection process, some decisions should be determined to achieve robust skin color segmentation. These decisions can be summarized into two points according to Appenrodt et al.[5], firstly, the selection of proper color model, and secondly, the feasible skin color model that fitted on the selected color model. On the other hand Schmugge et al. [8] and, Hasan and Mishra [10] included the parameters of the chosen color space to these steps, by using the fully components of the color model or dropping unwanted component.

2.1 Color Space Conversions and Selected Parameters

Usually all the images captured by camera(s)/ videos are in the RGB space [8], which consists of three primary color components (R, G, and B). Color space conversions used to convert pixel value from RGB color model into other color models or non- RGB color model as named by Schmugge et al. [8]. In this framework we have applied two color space conversions based on RGB color model, HSV, and YCbCr color spaces [19]. Transformations between RGB and other color spaces can be found in [20]. Since the components of each color model conclude luminance component which is variant according to lighting changes, some researches decided to neglect this parameter and utilize the chromaticity parameters only. According to studies [10][8], the color space can be define as 3D color when containing three components and 2D when removing the illuminance component [8]. The neglected brightness parameter is B for RGB and V for HSV and Y for YCbCr color spaces.

2.2 Histogram-based Skin Classifier

Histogram method considered as one of the non-parametric skin color modeling techniques that proved its usefulness in various fields such as image analysis [17]. Histograms represent colors distribution in the image by representing the components of the applied color space [17]. Histograms are used either with Bayesian classifier or look up table LUT [8]. The parameter of the modeling technique should be selected carefully, in histogram approach the bin width should be decided firstly [21].

Histogram probability are formulated into classes and color space components are quantized into particular number of bins [22][8] that contain the number of pixels encountered in the specific bin [22]. The training data are used to formulate the skin color distribution [13]. According to a study performed by Vladimir et al. [13] the histogram

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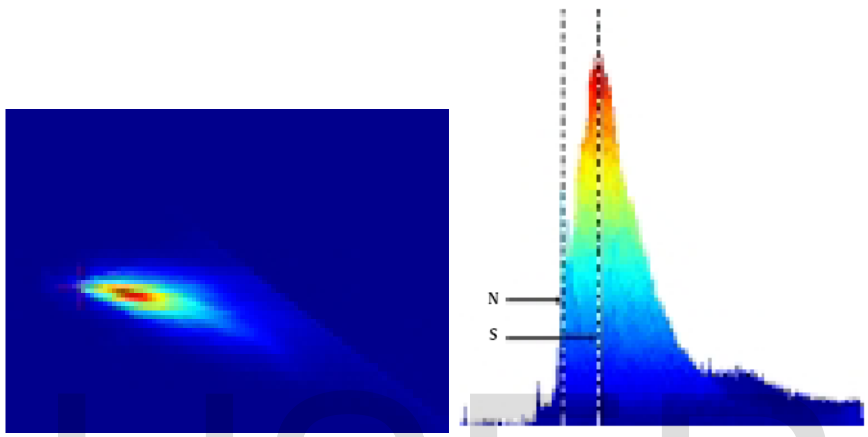
with LUT is widely used for face tracking purposes. Phung et al. [7] reveal that the performance of histogram improved when increasing the number of bin width.
Various studies applied RGB histogram with different number of bins, $32 \times 32 \times 32$ bins by Leonid [23], and $8 \times 8 \times 8$ bins by Reiner [24]. In work we applied $(8 \times 8 \times 8)$ which provides 512 bins. The HSV color space quantized into $18 \times 3 \times 3$ that forms 162 bins. Finally YCbCr color space quantized into $8 \times 4 \times 4$ which provides 128 bins.

In this work we used the chrominance parameters only for the utilized color spaces using LUT techniques. Figure 1 shows a pictorial representation for the histogram in r-g color space and a side view that demonstrates the skin and non-skin pixels distributions.



A B

Figure 1: Skin color histograms in r-g space (from [9]). A) r-g space. B) Side view of (A). N represents the peak of non-skin density and S represents the peak of skin density.

2.3 Proposed System Layout

The acquired input image is quantized into specific number of levels in 2D chrominance models as mentioned previously. The bin width for the r-g, HS, and CbCr are $((8 \times 8), (18 \times 3), \text{and}(4 \times 4))$ bins respectively using the lookup table technique LUT. The probability of histogram distribution h can be defined by equation (1) as mentioned in [13]:

$$h(c|skin) = \frac{skin\,(c)}{n} \tag{1}$$

Where $h(c|skin)$ represents the histogram probability which calculated as a ratio [8] of the value of each histogram bin for the skin color c, to the summation of all histogram bin n.

The proposed method inspired from the future work system adopted by Hasan [10], and [25] which build a skin color modeling system based on mixture of Gaussian Mixture Model, named (MiGMM) using three color spaces, RGB, HSV, and YCbCr. In this work we adopted mixture of histograms for skin color modeling system to segment the skin color of human hand regions instead of Gaussian Mixture classifier. In this framework we adopted a Mixture of Histograms Technique (MxHT) where the skin color based histogram modeling is applied for each color model, afterwards, the resulted histogram probability of each color model is evaluated by a weight value. The classification rate CR that is used to evaluate system performance are used as a measurement to calculate the weight that is assigned to each color model based histogram technique. The reason behind the selection of CR to represent the weight since obviously this metric represent the actual performance of the algorithm [25], equation (6) explains the CR definition. The mathematical representation of the MxHT is shown in equation (2):

$$P(c|skin) = \sum_{i=1}^{h} W_i \; h_i(c), \forall \, i = 1,2,..h \qquad (2)$$

Where W_i is the weight's value of the ith selected color space, and calculated by dividing the classification rate CR of the ith color model by the normalization of the CRs of all the utilized color models based histogram technique as shown in equation (3)

$$W_i = \frac{CR_i}{\sum_{i=1}^{h} CR_i} , \forall \, i = 1,2,..h \qquad (3)$$

and $P(c|skin)$ is the probability of pixel c being skin pixel using thresholding technique, where the pixel is classified as skin region if it is greater than specific threshold and classified as non-skin pixel otherwise. Threshold value is specified empirically. An overview of the proposed skin color modeling framework is demonstrated in Figure 2.

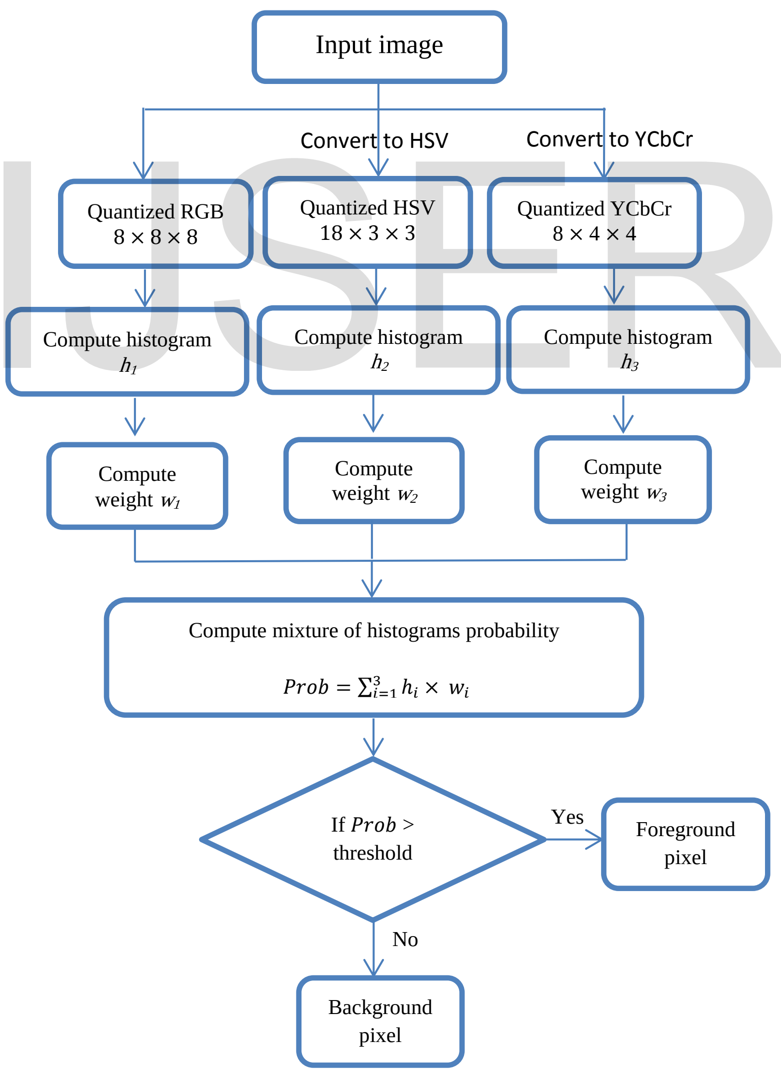


Figure 2: proposed system framework.

4. Related Contributions

The skin color is a perfect sign for the appearance of human in a particular scene [8]; however any variation in the background or illumination might leads to erroneous classification [26]. The fast and simple technique for segmenting skin pixels can be performed by applying the explicitly defined skin region method applied on a particular color space [16][26]. Osman et al. [26] adopted an explicitly defined skin region on RGB color model by adopting a new ratio rule for thresholding process [26], the TP and FP used for measuring system performance, the system achieved 94.91% in TP metric indicator. Raheja et al [27] simply performed color space conversions to segment skin pixel by converting to HSV color model. Michael and James [18] studied experimentally the performance of the histogram and mixture models in skin detection and conclude that the histogram superior in term of accuracy speed. The number of training images is 6822 images and 6818 for testing, and system performance measured using ROC curve. A spacious study done by Schmugge et al. [8] compared the performance of histogram and normal density approaches over nine color spaces: CIELAB, CIEXYZ, HIS, NRGB, SCT, YCbCr, YIQ, and YUV. They conclude that the neglecting the illumination parameter from color space reduces system performance [8], color model transformations are helpful tool and ameliorate system results [8], and of course the important role of modeling technique performed [8]. They inference empirically that the best performance achieved with the presence of illumination component on HSI or SCT color models using histogram technique on a large distribution size using indoor images [8]. Phung et al. [7] tested the performance of various color spaces, color quantization and classification techniques for analysis and comparison purposes and prepared a large database containing 4,000 color images with the ground truth images for skin and face segmentation [7], and extracted that Bayesian classifier with the histogram technique and the multilayer perceptron classifier outperforms on piecewise linear, single Gaussian, and mixture of Gaussian, however, the Bayesian classifier require more memory than other classifiers. Both Phung et al. [7], and Schmugge et al. [8] conclude that using only the chrominance components decrease the classification performance, and large bin width produce better results [7][8].

Hasan and Mishra [10] applied multiple of GMM over three color spaces RGB, HSV, and YCbCr, and extract the maximum Gaussian probability of each single color space to model the foreground and background pixels, and the classification rate was 98.825 for foreground and background modeling. Also the same authors, Hasan and Mishra in [10][25] suggest mixture of GMM over RGB, HSV, and YCbCr color spaces for hand gesture classification. Their system adopted a special weight value for each GMM color model. Terrillon et al [3] analyze the performance single Gaussian model and mixture of Gaussian on nine color spaces which are: normalized T-S, r-g and CIE-xy spaces, CIE-SH, H-S, I-Q, E-S, CIE-u*v* and CIE-a*b* spaces. They conclude that the distribution shape that depends on the color space used has great impact on the modeling technique used [3]. Mohammed et al [2] examined GMM on HSv and YCbCr color models and infere thar YCbCr has better performance than HSV.

Table 1: Comparative studies on classifications and different parameters applied for skin detection

Method	Classification Technique	Color Model	Background	Images used	Evaluation methods	Ground truth
Mohammed [2]	GMM	YCbCr and HSV	Fixed color	BAO and CALTECH database	Detection rate, False detection	No

					rate	
Appenrodt [5]	GMM	CbCr color model	Cluttered	36 isolated gestures (A-Z and 0-9)	TP/ FP and ROC curve	Yes
Phung [7]	Piecewise linear decision boundary, Baysian classifier with the histogram, Multilayer Perceptrons MLP, Gaussian classifiers	RGB, HSV, YCbCr, CIE-Lab and, rg, HS, CbCr, ab	Cluttered	4,000 color images	ROC curve	yes
Schmugge [8]	Histogram and normal density approaches	9 color spaces: CIELab, CIExyz, HIS, NRGB, SCT, YCbCr, YIQ, YUV.	Cluttered	845 images	ROC curve	Yes
Hasan [10]	Multiple of GMM	RGB, HSV, and YCbCr	Almost uniform	35 images for training/ 100 images for testing	CDR, FDR, and CR	Yes
Fang [14]	single Gaussian model	HSV color model	Cluttered	6 hand gesture images	No	No
Han [15]	SVM classifier based on active learning and region information	RGB color model	Fixed color	240 image frame from ECHO* database	CDR, FDR, and CR	Yes
Hasan [25]	Mixture of GMM	RGB, HSV, and YCbCr	Almost uniform	35 images for training/ 100 images for testing	CDR, FDR, and CR	Yes
Osman [26]	explicitly defined skin region	RGB color model	Almost cluttered	SIdb testing dataset/ two benchmark datasets, UChile and TDSD.	TP/ FP	Yes
Bergh [28]	Hybrid technique o Histogram and GMM	HSI and rg color models	Cluttered	10 gesture Images	N/A	N/A
Appenrodt [29]	GMM	CbCr color model	Cluttered	N/A	ROC curve	N/A

Phung[30]	GMM	YCbCr color model	N/A	100 color images for testing	ROC curve	

N/A: not Available.

5. Evaluation performance metric

There are two kinds of techniques to evaluate system performance, these techniques are, quantitative and qualitative techniques [26]. The quantitative technique require statistical measures such as calculating the classification rate or computing the receiver operating characteristic (ROC) curve analysis along with the TP and TN calculations [5][26][8]. While the qualitative technique measure the ability of the modeling classifier system to segment the image visually [26].

In our proposed system two quantitative methods of evaluation metric have been utilized for evaluating the performance of the proposed modeling system with other color segmentation modeling systems. The first method consists of three metrics; CDR, FDR, and CR. These metrics can be defined as follows [10][15][31]:
Correct Detection Rate (CDR): indicates the number of pixels that are correctly classified as skin pixel by the algorithm.

$$CDR = \frac{C_s^a}{T_s^g} \times 100\% \qquad (4)$$

False Detection Rate (FDR): indicates the number of pixels that are wrongly classified as non-skin pixel by the algorithm.

$$FDR = \frac{W_{ns}^a}{T_{ns}^g} \times 100\% \qquad (5)$$

Classification Rate (CR): indicates the number of skin pixels that are correctly classified by the algorithm and ground truth divided by the maximum value from either the number of skin pixels classified by the algorithm or the number of skin pixels classified by the ground truth.

$$CR = \frac{C_s^a}{\max(T_s^a, T_s^g)} \qquad (6)$$

Where C_s^a represent the total number of pixels classified correctly as skin pixels by the algorithm. T_s^g represent the total number of pixels classified correctly as skin pixels by the ground truth. W_{ns}^a represent the total number of pixels classified wrongly as non-skin pixels by the algorithm. T_{ns}^g represent the total number of pixels classified as non-skin pixels by the ground truth. and T_s^a represent the total number of pixels classified as non-skin pixels by the algorithm. Table 2 shows these metric parameters computed for the proposed algorithm and three color models.

Table 2: metric parameters for skin color based histogram approach

parameters	Histogram of rg	Histogram of HS	Histogram of CbCr	Proposed method MxHT
CDR	98.8910	99.3474	99.4345	99.2658

FDR	0.4433	0.2608	0.2260	0.2935
CR	98.8910	98.3485	97.8750	98.9349
Average	99.1129	99.1450	99.0278	99.3024

Table 2 shows experimentally performance results of applying the proposed system with the performance of single color space based histogram modeling method. Although the CDR metric in HSV and YCbCr is higher than the proposed system which represents the number of skin pixels that are correctly classified as skin pixel using these color spaces [10], the proposed system outperforms these techniques in the classification rate CR and hence the average performance of these parameters.

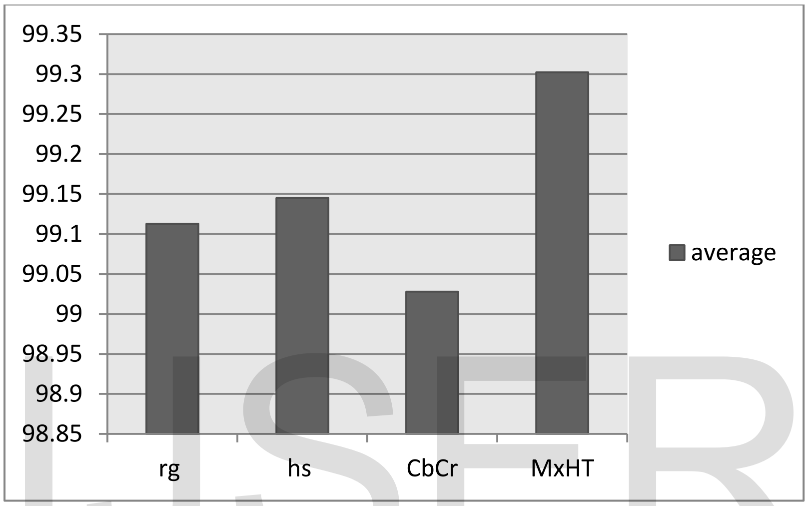


Figure 3: The average of metric parameters available in Table 2.

For fairly comparison with our proposed modeling system, we have also examined our proposed system with three different systems; 1) Multiple of Gaussian Mixture Model (MuGMM) technique from [10], 2) Mixture of Gaussian Mixture Model (MiGMM) technique from [10], 3) Multiple Histograms Technique (MHT) from [31], and 4) SVM classifier based on active learning [15].

Table 3: comparing the proposed method with other techniques

parameters	MuGMM [10]	MiGMM [10]	MHT [31]	SVM classifier [15]	Proposed method MxHT
CDR	99.3811	99.2195	99.1032	86.34	99.2658
FDR	0.2474	0.3120	0.3585	0.96	0.2935
CR	98.5928	98.9560	99.0850	76.77	98.9349
Average	99.2421	99.2878	99.2766	87.3833	99.3024

Table 3 demonstrates the performance evaluation of the selected systems with our proposed system. From table 2 we can notice that the CDR and FDR parameters have best performance results in Multiple GMM where the CDR achieved the maximum percentage and FDR achieved the minimum percentage over the compared techniques, however, the proposed system outperforms other techniques in CR and hence the average of the mentioned parameters.

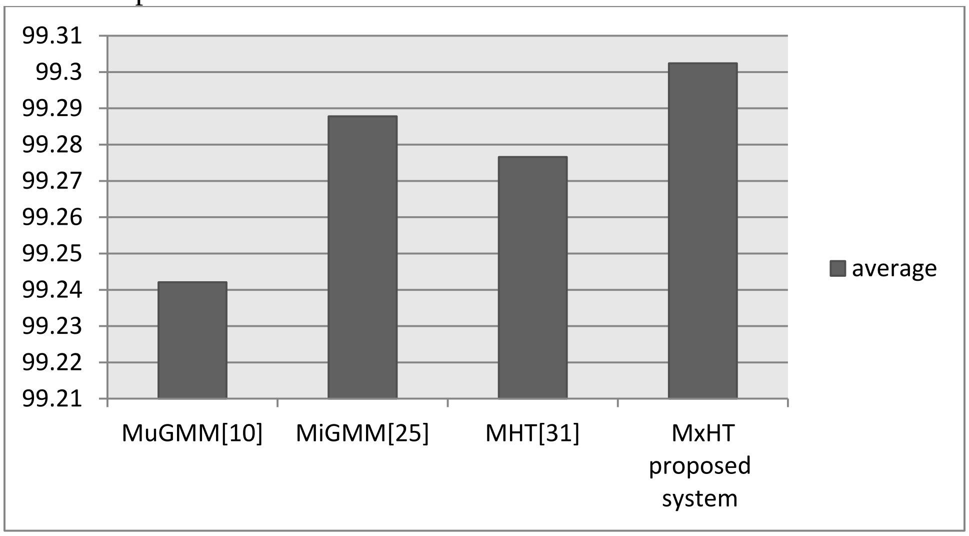


Figure 4: The average of metric parameters among different skin color modeling available in Table 3.

Some studies applied different metrics for the evaluation of their system performance, using the receiver operating characteristic curve analysis [5][7][8]. True Positive (TP) represents pixels that are classified correctly by the system and ground truth. True Negative (TN) represents pixels that are wrongly classified by the system and ground truth. False Positive (FP) represents pixels that are classified correctly by the system and wrongly by the ground truth. False Negative (FN) represents pixels that are classified wrongly by the system and correctly by the ground truth. Then the receiver operating characteristic (ROC) curve can be defined using the True Positive Rate (TPR), False Positive Rate (FPR) and the Accuracy (ACC), as defined [5]:

$$TPR = \frac{TP}{TP+FN} \tag{7}$$

$$FPR = \frac{FP}{FP+TN} \tag{8}$$

$$ACC = \frac{TP+TN}{TP+FN+FP+TN} \tag{9}$$

Generally, the segmentation algorithm with TPR metric close to 100% percentage and FPR metric close to 0% considered better for classification [5].

Table 4: performance of skin colour detection classifiers with the proposed system.

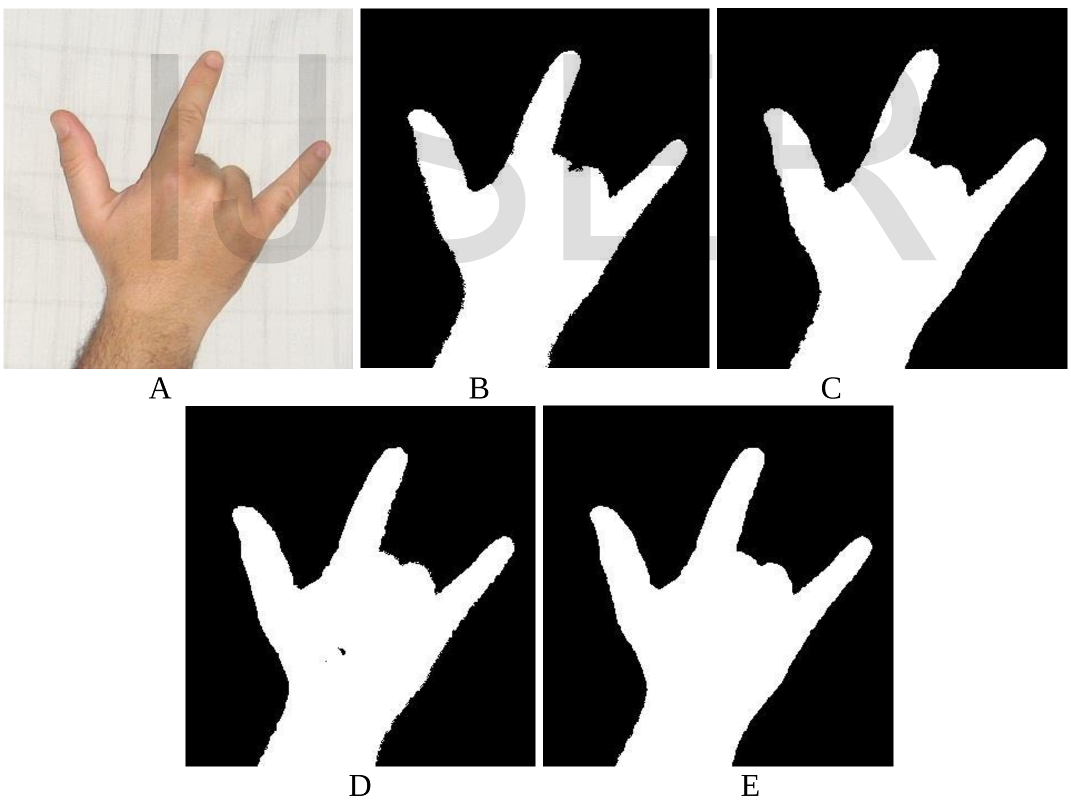
parameter	GMM [5]	MHT [31]	Proposed system MxHT
TPR	78.24	99.1032	99.2071
FPR	0.267	0.3658	0.4044

Accuracy	99.14	99.4825	99.4846
Average	92.371	99.40663333	99.4291

As seen in table 4, the best TPR metric achieved is by the proposed algorithm MxHT, although, the FPR metric has a higher value when comparing with other models, however, the proposed system outperforms on other systems in term of TPR and Accuracy by achieving the highest value. Although the average of our previous work multiple histogram technique [31] achieves results close to our proposed method outperforms but obviously the proposed system increase the performance of skin detection performance.

6. Experimental Results

For comparison reasons, in our system the same database used by [10], [25], has been utilized for empirical experiments evaluation. The used database included 35 images of hand gestures with different illumination changes for system training along with their ground truth images which are segmented manually, and the number of skin pixels used for system training is 757883 pixels. 100 gesture images are used for system testing. Figure 5 depicts some images of system implementation.



A) Original tested image, B) rgb, C) HSV, D) YCbCr, and E) the proposed algorithm.
Figure 5: An Example of implementing skin color detection of different color spaces based histogram with LUT and the proposed modeling technique

7. Conclusion

With the evolution of the communication especially between human and machines, the requirements to a robust skin color classification techniques are increased. In real time applications such as face/ hand detection and recognition, the accuracy factor play a major role besides the speed requirements. However, the complexion of the application imposes the suitable modeling system implemented and the proper color space utilized. In this work we used mixture of histograms with the LUT technique (MxHT) applied on multiple color models and calculate weight factor for each color model based histogram. As exhibited in the experiments the proposed system achieved promising results when comparing with different systems in the literature in term of accuracy and speediness. As noticed experimentally by study done by [7] and [8] the performance of the histogram with the Bayesian classifier using large bin width size and produce better results and the use of the color spaces using the three channels without removing the illumination channel can improve the modeling system performance. this will be our new orientation in the future work.

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