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Multiple Histogram Technique for Robust Skin Color Based Segmentation

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Abstract: With the spreading of the ubiquitous computing; a growing demand for vision based recognition and communication. The first step in the latter demand is the segmentation process. Pixel based segmentation techniques have been widely used in the field of pattern recognition. The actual information that can be extracted from pixel based techniques is the color. In this work statistical technique based non-parametric skin distribution method has been proposed for modeling skin color pixel by modeling histogram based skin color approach on several color models and then unifies all the models into single model to produce a superior model. The idea of the proposed work is inspired form Hasan [1] but in their work they applied parametric technique for modeling skin color distribution using Gaussian Mixture model (GMM). Three metric are used to evaluate system performance. The proposed system achieved 99.08 classification rate, and the output results proved that the proposed system outperforms on other systems that applied single histogram base skin color segmentation on each color model separately.

Keywords: *Skin Color, Segmentation, histogram, color space, normalized RGB, YCbCr, HSV.*

I. INTRODUCTION

Segmentation is the process of locating specific regions of interest [1]. Different segmentation techniques have been applied for this purpose, one of these techniques is pixel based segmentation method. Pixel based methods principle rely on the idea that pixels are sharing some characteristics such as color in the same region [2]. Pixel based skin color segmentation methods witnessed widely diffusion in the fields of computer vision, pattern recognition [3], and image retrieval [4]. For gesture recognition systems, an accurate and robust segmentation are demanded [3] since it represent the first crucial step for recognition system. The pixel color considered as the most popular cue that provide an efficient classifying of the segmented region [5], where each pixel is classified into skin and non-skin pixel according to its intensity [3].Although, the advantages of skin color segmentation methods, its invariance to size [6], and orientation[6], besides its assistance in face and hand video tracking [6] and can minimize the search space by seeking for the skin color only [1], it suffer from misclassification under variant illumination changes and occlusion with some other body parts such as face and arms [6][3]. However some restrictions on the user/ camera position [6][5]can reduce this problem. For building human skin color segmentation system, two consideration such be taken into account. Firstly, the selection of the color space, and secondly, reliable skin color modeling method [1][5]. Different statistical algorithms have been applied in pixel based skin color detection methods, varying from thresholding technique such as Explicitly defined skin region [1][5] to parametric model such as single Gaussian Model (GM) and Mixture of Gaussian Model or Mixture Gaussian Model (GMM), and non- parametric model such as histogram based lookup table (LUT) [5][1], and Bayes classifier. Each of the mentioned skin color modeling methods has different merits and the nature of the application determine the selection of the reliable modeling method and the perfect color space that fit with the selected skin color modeling method.

II. RELATED WORK

For the segmentation of skin color pixels, various techniques have been proposed. Some researches analyzed the skin color information for skin color detection by converting into different color space such as normalized r-g, HSV and YCbCr. Techniques including parametric and non-parametric methods usually deal with the chrominance plane components of the color only and neglect the luminance component [6], to minimize the effecting of lighting ambient changes [6][5] and the overlapping with other background objects [6].GM and GMM are parametric methods that model the distribution of skin color to classify the skin color, using some parameters mean, variance, and weights (in case of GMM method). These parameters initially extracted either from predefined training data set [1], or using some statistical method such as Expectation Maximization (EM) [7] or k-mean clustering [8]. However, the parameters should selected in prudence where bad initial estimation of GMM parameters can led to unpredictable classification results, as well as the increasing number if GMM mixtures considered computation / time [4] consuming and produce infeasible system [6]. On the other hand non-parametric methods provide general distribution of the color [6]. Lookup table (LUT)is a histogram based method [9] in which the probability of the skin color can be estimated using only the training data and no need for explicit model fitting[1][5][10] . Histogram one of the non-parametric methods that evaluate the probability density function of image intensities [6][11]by counting pixel frequencies of each color [11]. In this method, the color space components are partitioned or quantized into regular number of bins for simplicity and robust performance [10]. The non-parametric methods are fast [5]and efficient when adequate amount of training data are ready [6], however, insufficient amount of training data led up to inaccuracy of skin color distribution [6][11]. Hasan [1] proposed multiple of GMM system (MuGMM) on three different color models, i.e. normalized r-g, HSV, and YCbCr for modeling hand skin color. Hasan applied a separate GMM for each color model and obtained a probability for each color model and the maximum probability have been utilized as the final probability. Bayesian decision rule were used for classifying the skin pixels.[4]proposed segmentation method based on GMM by utilizing the property of converting gray-level image values into different modes of histogram [4], and built a normal distribution for each mode. The number of histogram modes as well as the GMM parameters has been estimated using EM algorithm[4]. [12] applied histogram back projection skin color model for face detection algorithm, HS color space are used to build the system and thresholding technique used to obtain the segmented binary image [12]. [13] suggested histogram-based self-constructing neural fuzzy inference network (SONFIN) system for Skin color segmentation, using HS color space [13]. The suggested system used HS Histogram information for training the SONFIN [13]. However, histogram-based approaches usually need great amount of training data [9][5], hence a large space for memory storage [9] which would already increase when the size of training data increase [6h]. [8] Gokalp applied GMM for modeling human skin color distribution. K-means algorithm is used for parameters initialization, EM algorithm for parameters estimation, and Minimum Description Length (MDL) algorithm for determining the number of GMM parameters. Using three different color models YES, chromatic space and log-opponent models [8]. [14] adopted YCbCr color space with GMM for skin color segmentation of hand gesture and test the efficiency of three different types of cameras (single color, stereo color and thermal camera) for better segmentation.[15] Studied different histogram bins and concluded that the best number of histogram bins for RGB color model is $32 \times 32 \times 32$ for a small amount of training data [15].

III. PROPOSED ALGORITHM

This work inspired from the method of [1] which build a skin color modeling system based on multiple Gaussian Mixture Model (MuGMM) from the most common three color spaces, as mentioned previously. In this work we adopted multiple histograms skin color modeling system to segment human skin color regions. The proposed system combine three color models, RGB, HSV, and YCbCr to produce a robust skin color model which can take advantages of the selected color spaces. In this system a histogram based approach has been applied on each color model, and then all the resulted histograms are integrated to form a new superior histogram technique called Multiple Histograms Technique (MHT).The proposed model has shown its efficiency when compared with histogram based approach applied on single color model. From the selected color models, only the chrominance components are utilized in the proposed system. The chrominance components are quantized into significant number of bins [5] that represent the range of color values [5] in an image region [16]. The 2D histogram are generated from these bins which are formed the lookup table LUT [5]. Each bin has the number of frequencies a specific color pixel appeared; this process is performed in the training stage of skin color to extract the probability distribution of skin color pixels [5].The RGB histogram divides each of the RGB components into eight number of bins as in [10], this provide a $(8 \times 8 \times 8)$ histogram of 512 bins. Different study applied histogram on RGB color model and selected $32 \times 32 \times 32$ bin histograms [6]. In this work we applied the $(8 \times 8 \times 8)$ bins histogram.

The HSV histogram divides into eighteen regions for (H) component and three regions for the (S, V)components, this provide $18 \times 3 \times 3$ histograms of 162 bins.

The YCbCr histogram divides the (Y) luminance component into eight regions, and (Cb, Cr) the chrominance components into four regions, which form $8 \times 4 \times 4$ histogram of 128 bins as in [16]. As mentioned previously only the chrominance components are used (RG, HS, and CbCr) components to reduce the illumination change by removing the luminance component.

For a single color model histogram, the probability distribution p can be defined by equation (1) as mentioned in [5]

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

Where $skin\ (c)$ represent the value of histogram bin for the color vector$c$,and n represents the sum of all values of histogram bin.

The proposed system can be defined by equation (2)

$$h(c|skin) = \max_{i\,\in\,I} h_i(c) \qquad (2)$$

WhereI represent the number of color models used (which considered three color models in this study),h_i represents the histogram probability of the color model i,h(c|skin) represent the probability of color c being a skin color pixel.

The skin color c is classified into skin or non-skin pixel using a thresholding technique. Empirically the value of the threshold is specified.

IV. EVALUATION OF SEGMENTATION RESULTS

For the proposed method, metric have been adopted to evaluate the result [1].The same data base applied in Hasan [1] are utilized in this work35 images are used for training the system with their ground truth images, the number of skin pixels used for system training is 757883, and 100 images are used for the testing phase. The first metric as described in [1]:

Correct Detection Rate (CDR): Represents the number of pixels that are correctly classified as skin pixel by the algorithm.

$$CDR = \frac{C_s^a}{T_s^g} \times 100\% \qquad (3)$$

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

$$FDR = \frac{W_{ns}^a}{T_{ns}^g} \times 100\% \qquad (4)$$

Classification Rate (CR):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.

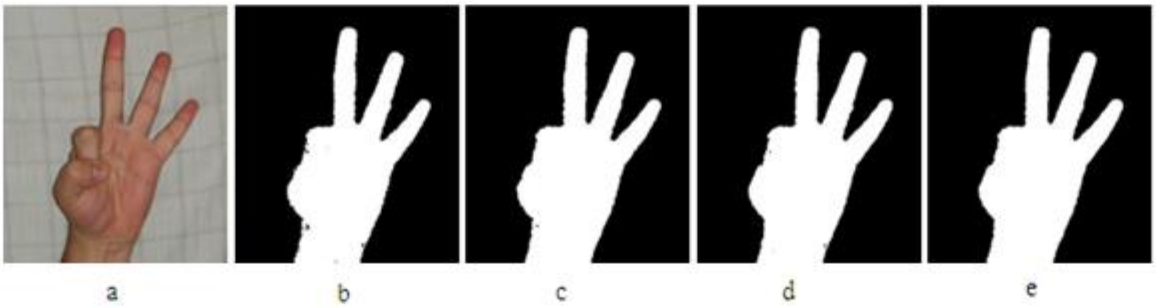
$$CR = \frac{C_s^a}{\max(T_s^a, T_s^g)} \qquad (5)$$

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^arepresentthe total number of pixels classified as non-skin pixels by the algorithm. Table 1 shows these metric parameters computed for the proposed algorithm and three color models.

Table 1: metric parameters for classification rate of skin color based histogram approach

parameters	Histogram of RGB	Histogram of HSV	Histogram of YCBCr	Proposed method HMCM
CDR	97.3599	98.4557	98.4743	99.1032
FDR	1.0554	0.6173	0.6099	0.3585
CR	97.3599	98.4557	98.4743	99.08507
Average	97.88813333	98.7647	98.77956667	99.2766

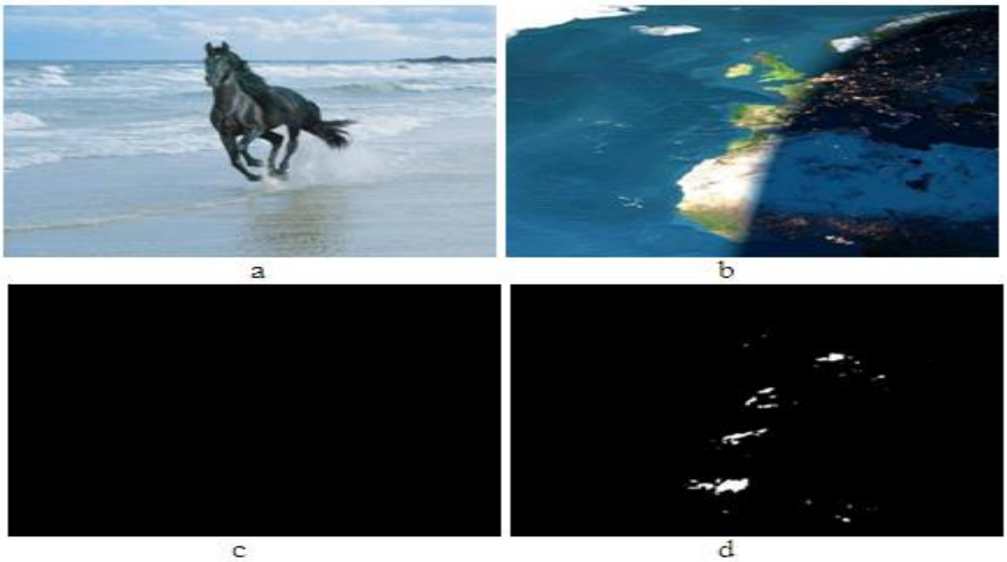
From table 1, obviously the result of the proposed algorithm is superior and outperforms on other color models when applying single color model based histogram approach comparing all the metric parameters separately. Figure 1demonstrates some results when applying the proposed algorithm on different hand gesture images.



a) the original input image, b) rgb, c)HSV, d)YCbCr, and e) the proposed algorithm.

Figure 1: An example of implementation the histogram based skin color segmentation on the selected color models and the result of the proposed algorithm.

From the Figure 1, we can notice that the segmentation result for each of the RGB and YCbCr color models have some shortcoming in specific regions, while the results using HSV are mostly perfect, hence the proposed algorithm take the advantages of the selected color models, the result of the proposed algorithm represents the histogram based skin color applied on HSV color model results. We applied the proposed algorithm on a natural image with no kin color pixels, and the results are explained in Figure 2.



a, b) the input images, c, d) the corresponding segmented images using the proposed algorithm for each of a and b respectively.

Figure 2: the implementation of the proposed algorithm on natural scene.

V. CONCLUSION

Skin color based segmentation techniques have been widely utilized in pattern recognition and computer vision fields. Various color space are employed with skin color based segmentation algorithms depending on the application field. The separation of the chrominance components from the illumination component provides the benefit of avoiding sensitivity to illumination changes. Statistical approaches have proven its robustness in the field. In this work, we proposed a histogram based skin color segmentation system, this system take the advantage of applying histogram based skin color segmentation for several color models and combine them to unify a single modeling system. The proposed system is fast, efficient and the output results show its robustness and outperforming on other color models.

VI. FUTURE WORK

The idea of the future work are inspired also form the idea of Hasan [1] but he applied Gaussian mixture Model GMM for modeling the skin color as well, in this work we utilize histogram method for modeling the skin pixel. In this work, the maximum of histogram skin color based segmentation have been proposed as shown in equation (2). The future work is to build modeling system based histogram skin color segmentation technique by using the Mixture of multiple histogram technique (MiMHT), where each separated color model applied on histogram based approaches are evaluated by a weight value. The weights for each color model are represented by the classification rate (CR) defined in equation (5) in which it represent the exact representation of the model efficiency. Equation (6) explained the proposed system:

$$P(c|skin) = \sum_{i=1}^{I} W_i \, h_i(c) \tag{6}$$

Where W_i represents the weight's value of the ith selected color model. The value of the weight can be calculated form the normalization of the classification rates CR of the utilized color models as shown in equation (7)

$$W_i = \frac{CR_i}{\sum_{i=1}^{I} CR_i}, \forall\, i = 1,2,..I \tag{7}$$

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