Melting of Multiple GMM and Multiple Histogram in Segmentation, Gesture Recognition

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Abstract

In order to visualize the objects in the surrounding environment; an eye is needed, in this case the human can recognize the objects that are in touch every single day, but, however, in the era of the computer domination and specially in the area of human-computer interaction, we have to provide the something similar to the eye function which is the basic and primary step in visualizing every single object, that is the segmentation. Vast methods are used for segmentation process some of them are useful and others are error-generated, however, speaking on the GMM, these segmentation methods uses single model to tone the feature area of the targeted segmentation object, in this method, we have applied multiple of GMM to reduce the error resulted from such modulation and to obtain promising results, these results are compared with the application of multiple histogram technique by simulating the feature area of the skin color in multiple probability table; each feature area has a single probability table and all combined using one formula. We have adopted in this paper four different color models which have good reputation in extracting of skin color which are normalized RGB (rgb), HSV, YCbCr.

Keywords: Segmentation techniques, Gaussian mixture model, GMM, Bayesian decision rule, mixture of GMM, skin color segmentation, color based segmentation, GMM for skin color, multiple of GMM, Gesture recognition, hand gesture.

I. INTRODUCTION

One of the outstanding applications of the segmentation application is to detect the objects that can be used in the sign-language application, in which the well-detected object will undergo under recognition steps to facilitate the computer recognition, one of its application is for hearing impaired people [1]. However, the gesturing is rooted in our life and it is used widely in each single day even if the person is speaking on phone [2] and we can see that the mouse and keyboard are replaced with human-body limbs [3] and the attention is focused on those new input devices [4], which characterized by connection-less [4][5], powerful [6] promising [7] and simulate the natural behavior [8] and used for augmented reality as well [9][10] and eventually, non-spoken language [11][12], but the important issue is to locate the hand correctly [13].

Sometimes, and to start the segmentation process, an initial hand location is required [7], skin color-based and haar pattern-based [7] can be applied, but, however, in the cluttered scenes and varying lighting conditions this initial location is important [14], so the manual detection is applied [7], however, for occluded and partially disappeared objects, the tracking is useful as well [9], furthermore, other review studies can be found in [15][18][21][22][23].

The color is composed of two main parts, chrominance which represented by melanin pigment and the luminance [16], the luminance is neglected in this work since it is a variable parameter and reflected according to illumination condition, but, however, the chrominance can be considered as reliable parameter.

II. IMAGE SEGMENTATION

The primary objective of the image segmentation technique is to classify the regions in better way [17]. For any image segmentation process; two general methods can be applied as a guidance for classification procedure [17]:

1- Discontinuity: Searches for sharp change in the image intensity to detect the edges of a specific object.

2- Similarity: Searches for similar values (color values) between neighbor pixels to join specific image regions.

III. SEGMENTATION PARAMETERS - MULTIPLE OF GMM

The main direction of this paper is to divide the feature area of the skin-color using three color models as mentioned above by neglecting the luminance component of the skin-color, after that; each division of the feature area is modeled using single GMM and all combined together using one formula [19].

Similarly, those feature-area of the extracted skin-color features are modeled using single histogram probability table for each single division [20], and the performance of both of them are compared together.
The mathematical model in this case can be seen as in Equation 1.

\[ P(c|\text{skin}) = \max_{m \in M} g(c; \mu_m, \Sigma_m) \]  

Where \( M \) is the number of color models employed, \((\mu_m, \Sigma_m)\) are the parameters associated with color model \( m \) necessary for single GMM modeling, and \( g(c; \mu_m, \Sigma_m) \) is GMM known, and \( P(c|\text{skin}) \) is the probability of color \( c \) being a skin color.

The probability of color \( c \) being non-skin color which is written as \( P(c|\neg\text{skin}) \) can be modeled the same as Equation 1 but the corresponding parameters should be adopted, however, in order to decide whether this color \( c \) is a skin color or none; a threshold should be decided, we have adopted a Bayesian decision rule for finalizing this decision as Equation 2.

\[ \frac{P(c|\text{skin})}{P(c|\neg\text{skin})} > \xi \]  

Where \( \xi \) is a threshold which is normally has the value of one and the color \( c \) is belonging to skin class if this holds, however, this latter parameter can be adjusted in case of the background has not been modeled by assuming that \( P(c|\text{skin}) = P(c|\neg\text{skin}) \), furthermore, Bayes’ rule can be adopted as well for determining the probability of current skin color \( c \) belongs to skin class as shown in Equation 3.

\[ P(\text{skin}|c) = \frac{P(c|\text{skin})}{P(c|\text{skin}) + P(c|\neg\text{skin})} \]  

And similarly, Equation 4 used to determine the probability of current color \( c \) belongs to non-skin class.

\[ P(\neg\text{skin}|c) = \frac{P(c|\neg\text{skin})}{P(c|\text{skin}) + P(c|\neg\text{skin})} \]  

IV. SEGMENTATION PARAMETERS - MULTIPLE OF HISTOGRAM

For a single color model histogram, the probability distribution \( p \) can be defined by equation (5) as mentioned in [20]

\[ h(c|\text{skin}) = \frac{\text{skin}(c)}{n} \]  

Where \( \text{skin}(c) \) 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 (6)

\[ h(c|\text{skin}) = \max_{i \in I} h_i(c) \]  

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

By using the thresholding technique, the skin and non-skin pixel can be classified accordingly.

V. PERFORMANCE EVALUATION CRITERIA

A. Correct Detection Rate (CDR)

The percentage of the pixels that are classified correctly by the algorithm as skin pixels.

\[ \text{CDR} = \frac{\text{C}_s}{\text{T}_s} \times 100\% \]  

B. False Detection Rate (FDR)

The percentage of the pixels that are classified wrongly by the algorithm as non-skin pixels.

\[ \text{FDR} = \frac{\text{W}_n}{\text{T}_n} \times 100\% \]  

C. Classification Rate (CR)

The number of classified skin pixels correctly by the algorithm and ground truth divided by whichever maximum of each of number of skin pixels classified by the algorithm and number of skin pixels classified by the ground truth.

\[ \text{CR} = \frac{\text{C}_s}{\max(\text{T}_s, \text{T}_n)} \times 100\% \]  

Where \( C_s \) is the total number of pixels that correctly classified as skin pixels by the algorithm, \( T_s \) is the total number of pixels that classified as skin pixel by the ground truth.
truth, \( W_{ns} \) is the total number of pixels that are classified wrongly as non-skin pixels by the algorithm. \( T_{ns} \) is the total number of pixels that are classified as non-skin pixels by the ground truth, and finally, \( T_{s} \) is the total number of pixels that classified as skin pixel by the algorithm. Table 4 shows the different values of these parameters.

VI. RESULTS

As demonstrated by the following table 1 which illustrated the application of segmentation process using each of rgb, HSV, YCbCr each one alone and the proposed technique in [19] which is multiple of GMM, the performance of this proposed algorithm is higher and can give most promising results.

Similarly, table 2 shows the application of Multiple histogram with their corresponding values.

![Figure 1: Pictorial Comparison between the overall performance between each of MuGMM and Multiple Histogram.](image)

Table 1: Multiple GMM Experiment Results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>MuGMM</th>
<th>GMM of normalized RGB</th>
<th>GMM of HSV</th>
<th>GMM of YCbCr</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDR</td>
<td>99.873</td>
<td>99.652</td>
<td>97.937</td>
<td>98.402</td>
</tr>
<tr>
<td>FDR</td>
<td>0.474</td>
<td>0.441</td>
<td>0.115</td>
<td>0.188</td>
</tr>
<tr>
<td>CR</td>
<td>98.825</td>
<td>98.903</td>
<td>97.937</td>
<td>98.402</td>
</tr>
<tr>
<td>Average</td>
<td>99.408</td>
<td>99.371</td>
<td>98.586</td>
<td>98.871</td>
</tr>
</tbody>
</table>

Table 2: Multiple Histogram Experiment Results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Multiple Histogram</th>
<th>GMM of normalized RGB</th>
<th>GMM of HSV</th>
<th>GMM of YCbCr</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDR</td>
<td>99.1032</td>
<td>97.3599</td>
<td>98.4557</td>
<td>98.474</td>
</tr>
<tr>
<td>FDR</td>
<td>0.3585</td>
<td>1.0554</td>
<td>0.6173</td>
<td>0.6099</td>
</tr>
<tr>
<td>CR</td>
<td>99.08507</td>
<td>97.3599</td>
<td>98.4557</td>
<td>98.474</td>
</tr>
<tr>
<td>Average</td>
<td>99.2766</td>
<td>97.8881333</td>
<td>98.7647</td>
<td>98.779</td>
</tr>
</tbody>
</table>

As a final chart that can demonstrate the performance of each of the adopted technique, CDR, CR and average are included in the following figure to reveal the unobserved performance of each in one chart as following:

VII. CONCLUSION

As seen in the previous study, the overall performance of the statistical method which is histogram probability is seem better in the area of the segmentation process since it given probability for each single pixel of the targeted image or object, while the GMM simulate the entire area with hypothetical oval shape regardless the number of models falls inside since some of the pixels within that oval may be actually non-skin pixels but because their accidental location they classified as skin-pixels, however, using multiple models for modeling skin feature area with the help of GMM has an edge on single modeling since the error in this case is reduced as compared with single model, and can enhance the overall performance of the adopted color model used.

REFERENCES


