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COLOR DETECTION USING GAUSSIAN MIXTURE MODEL

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ABSTRACT

In this paper, we propose a method for color region detection in color images and videos. It is based on Gaussian mixture model (GMM) which is calculated by the expectation-maximization (EM) algorithm. We assume that we know the number of Gaussian components in the reference image, but we do not know it in input images. The proposed our approach is composed of two steps. We first estimate GMM parameters using EM algorithm over a reference image including colors regions of interest (ROI). To construct 2-dimensional GMM in the reference, we consider two chrominance features, CbCr-channel from YCbCr color model. The second step is to detect and segment the color regions by using GMM parameters in input images. We decide the color regions by the posterior probability which is Gaussian distributions calculated by GMM in the reference image. Our method can only detect and segment the colors ROI including the Gaussian components from the input image. The experimental results show that it is very effective to detect the predefined multi-colored regions in images and videos.

Keywords: *Gaussian mixture model (GMM), expectation maximization (EM), YCbCr color model, Color region detection, Segmentation*

1. INTRODUCTION

Most of images and videos are captured and stored by various color formats. In computer vision applications such as image retrieval, video surveillance, object tracking, pattern recognition, robot vision system, color provides more information than gray scale. We are easily able to perceive objects or regions by color. Therefore, it is an important and useful feature that can be used for detecting and segmenting a region of interest from images and videos. In general, for color image segmentation and detection, we need to calculate color features based on color space models such as HSV, YCbCr, HLS and Lab, and then the distribution of the color features is calculated to localize color regions.

In this paper, we propose a method for color region detection in color images. It is based on Gaussian mixture model (GMM) which is calculated by the expectation-maximization (EM). We assume that we know the number of Gaussian components in the reference image, but we do not know it in input images. The proposed approach is composed of two steps. In the first step, we estimate GMM parameters using EM over a reference image including colors regions of interest. To construct 2-dimensional GMM in the reference image, we consider two chrominance features, CbCr-channel from YCbCr color space model. The second step is to detect and segment the color regions in input images by using the GMM parameters extracted from the reference image. We classify the color regions as pixel-wise approach by the posterior probability which is Gaussian distributions calculated by the GMM parameters. Our method can only detect and segment the colors regions of interest including the Gaussian distribution components of colors from input images.

The remainder of the paper is organized as follows. Section 2 describes related work. Section 3 presents our color region detection method. Section 4 presents experimental results in an image and a video. Section 5 contains conclusions and future work.

2. RELATED WORK

Color detection is still challenging tasks in image processing and computer vision fields. There are some surveys on color image segmentation [1-5]. A simple method for color segmentation is to use in-range color values that include a predetermined minimum color value and a maximum color value [6-8]. It is a simple and effective approach, but it cannot handle a little more complicated color distribution. Hasan Fleyeh

[8] uses in-range values in HLS color model for detection and segmentation of road and traffic signs. There are several skin color detection approaches by using statistical color modelling [9-14]. Color distribution can be estimated by histogram [15-19], covariance [20], K-means clustering [21-26], fuzzy C-means clustering [27-29], GMM [30-40]. Though there are many color segmentation techniques, they focus on segmentation an image into a given number of clusters or regions. We present a method by using GMM for color region detection in color images and videos.

In this paper, we provide colors of interest in a reference image, and estimate the distribution by considering two chrominance features, CbCr-channel from YCbCr color model using GMM, and then detect color regions of interest in an input image and video. It can be effectively detecting the predefined colors or the color regions of interest which are given by user in images and videos.

3. THE PROPOSED COLOR DETECTION METHOD

Flow chart of our proposed color region detection is shown in Figure 1. It is based on GMM [31, 32, 33, 34, 35, 39, 40].

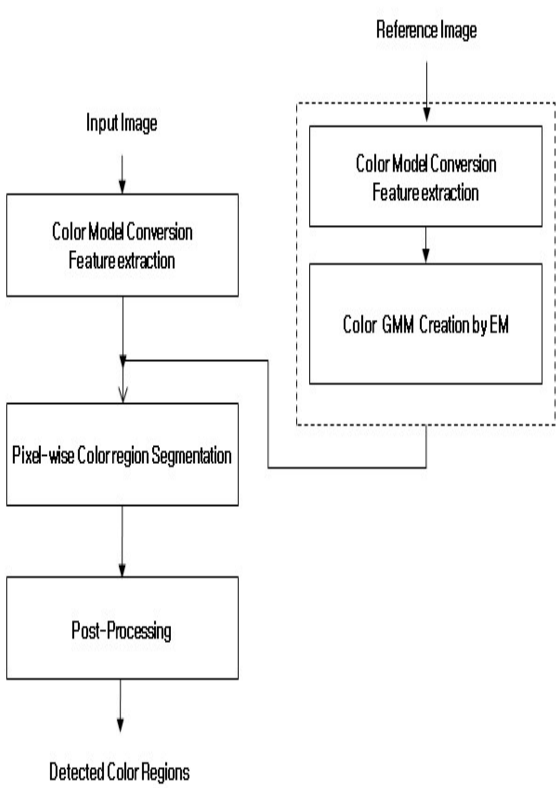

Figure 1: Flow chart of the proposed approach

We estimate GMM parameters using EM over a reference image including colors of interest which are provided by user. To calculate GMM parameters of a reference imager, we consider two chrominance features, CbCr-channel from YCbCr color model. To detect and segment color regions by using GMM in input images, we classify pixels in an input image into the color class which is based on the maximum likelihood based on GMM. The likelihood is calculated by using the estimated Gaussian distribution parameters.

3.1 Color and Features

RGB images captured from a camera are converted as YCbCr color model by using equation (1). We extract two color features, CbCr-channel to estimate color distributions in a reference image. Cb and Cr are the blue-difference and red-difference chrominance component. Y-channel which is luminance is not used for making robust against light intensity.

$$Y = 0.299R + 0.587G + 0.114B \quad (1)$$
$$Cr = (R - Y)0.713 + 128$$
$$Cb = (B - Y)0.564 + 128$$

3.2 Gaussian Mixture Parameter Estimation

GMM is a weighted sum of K-Gaussian components, as in equation (2). X is a 2-dimentional color feature vector, X = [Cb, Cr], extracted by CbCr-channel. $w_k, k = 1,...K$, are the mixture weights, and $N(X \mid u_k, \sum_k), k = 1,...K$, are the 2-dimensional Gaussian distribution components with mean vector u_k and covariance matrix $\sum_k$.

$$p(X \mid \lambda) = \sum_{k=1}^{K} w_k N(X \mid u_k, \textstyle\sum_k), \quad (2)$$

$$\text{where } \sum_{k=1}^{K} w_k = 1, 0 \le w_k \le 1$$

$$N(X \mid u_k, \textstyle\sum_k) = \frac{1}{(2\pi)|\sum_k|^{1/2}} \exp\left\{-\frac{1}{2}(X - u_k)' \textstyle\sum_k^{-1} (X - u_k)\right\}$$

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We can estimate the parameters of the GMM, $\lambda = (w_k, u_k, \sum_k)\ k = 1,...K$ by using EM algorithm based on maximum likelihood (ML) estimation of equation (3).

$$\ln p(X \mid \lambda) = \sum_{i=1}^{N} \ln\left(\sum_{k=1}^{K} w_k N(X \mid u_k, \textstyle\sum_k)\right)$$

The following algorithm is a summary for calculating GMM parameters by EM algorithm [32-34]. Input color feature vectors, $x_i,\ i = 1,...N$ are 2-dimentional color feature vectors (Cb, Cr) which are extracted from a reference image. Output is the parameters of GMM.

Algorithm: Calculation of GMM parameters by EM algorithm
Input: $x_1,...x_N$, 2-dimensional color feature vectors from a reference image,
Output: K Gaussian parameters

$$\lambda = (w_k, u_k, \textstyle\sum_k), k = 1,..., K$$

Step 1: Initialize parameters,

$$u = (u_1,..., u_K)$$
$$\textstyle\sum = (\sum_1, ..., \sum_K)$$
$$w = (w_1,..., w_K)$$

and calculate the log-likelihood by equation (3).

Step2: Expectation step
For each feature vector $x_i,\ i = 1,...N$, $\gamma(z_{ik}),\ i = 1,...K$ is calculated by equation (4).

$$\gamma(z_{ik}) = \frac{w_k N(x_i \mid u_k, \sum_k)}{\sum_{j=1}^{K} w_j N(x_i \mid u_j, \sum_j)} \quad (4)$$

where $\sum_{k=1}^{K} \gamma(z_{ik}) = 1$

Step3: Maximization step
Update Gaussian parameters, $\lambda = (w_k, u_k, \sum_k)\ k = 1,...K$

$$u_K = \frac{1}{N_k} \sum_{i=1}^{N} \gamma(z_{ik}) x_i \quad (5)$$

$$\textstyle\sum_k = \frac{1}{N_k} \sum_{i=1}^{N} \gamma(z_{ik})(x_i - u_k)(x_i - u_k)^T \quad (6)$$

$$w_K = \frac{N_k}{N} \quad (7)$$

where $N_K = \sum_{i=1}^{N} \gamma(z_{ik})$

Step4: Calculate the log-likelihood by equation (3). If it converges then stop, else go to Step 2.

3.3 Color Region Classification

The Gaussian distribution components $N(X \mid u_k, \sum_k)$, $k = 1,...K$ are estimated by using color features, CbCr-channel extracted from a reference image given by user. We consider that each Gaussian $N(X \mid u_k, \sum_k)$ represents the class C_k which is the color region.

We classify each pixel in an image by using equation (8) which is based on the maximum likelihood. If the probability at each pixel is less than a threshold T, then we decide it as the color which is not in a given reference image. If the probability at each pixel is greater than a threshold, we decide it as the class with the maximum likelihood.

$$\begin{aligned} &x \notin \forall C_i \ \ if\ N(X \mid u_i, \textstyle\sum_i) < T \\ &x \in C_i \ \ if\ N(X \mid u_i, \textstyle\sum_i) > N(X \mid u_j, \textstyle\sum_j)\ and \\ &\qquad N(X \mid u_i, \textstyle\sum_i) > T,\ \forall j \neq j \end{aligned} \quad (8)$$

4. EXPERIMENTS AND RESULTS

Experiments show that our proposed method effectively detects the red and green color in images and videos. All images and videos are captured by using a smartphone camera. Their resolutions are 640x480 24bits. They are captured as BRG format and then convert them to YCrCb.

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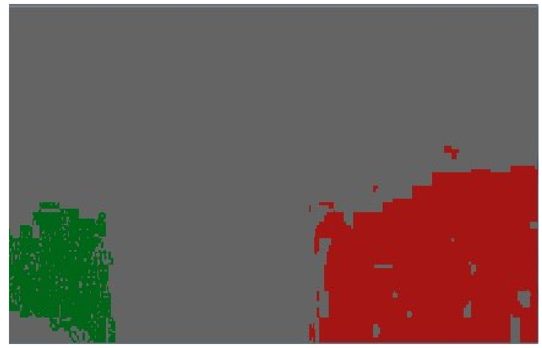
The software is implemented by using Python and OpenCV. We use 3-Gaussian mixture components in GMM. Figure 2(a) is a reference image which has 2 colors (green and red) that we want to detect. Equation (9) shows the calculated GMM parameters.

$$
\begin{aligned}
w_1 &= 0.4044586 \\
\mu_1 &= [\,199.57504921 \;\; 102.73769885\,] \\
\Sigma_1 &= \begin{bmatrix} 0.28229875 & 0.01673289 \\ 0.01673289 & 0.22599627 \end{bmatrix} \\
w_2 &= 0.5955414 \\
\mu_2 &= [\,83.70280895 \;\; 105.90842246\,] \\
\Sigma_2 &= \begin{bmatrix} 0.37719641 & -0.01212757 \\ -0.01212757 & 0.18528081 \end{bmatrix}
\end{aligned}
\tag{9}
$$

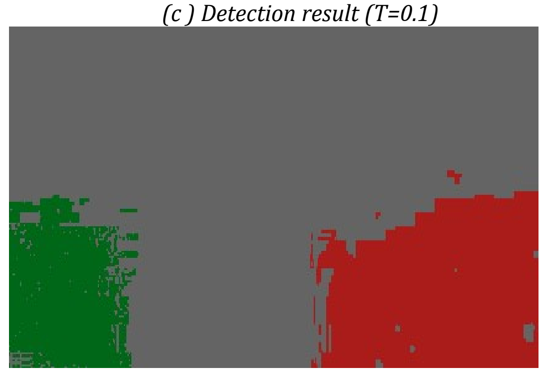
Figure 2(b) is an input image which has 3 colors (green, red, and gray background) and is blurred a little in borders. Figure 2(c) and Figure 2(d) are the detected results using the probability threshold value in equation (8), T=0.1, T=0.01, T=0.0001 and T=0.000000001, respectively. It shows that the threshold value should be very small value for detecting colors at the boundary region. We use T=0.000000001 as the threshold value in the following experiments. In detection results of Figure 2(c)-2(f), if the class probability at each pixel is less than the threshold T, then it is displayed as the gray color, RGB=(100, 100, 100) and regions with the red and green color are displayed as the average color of the regions.

(a) Reference image

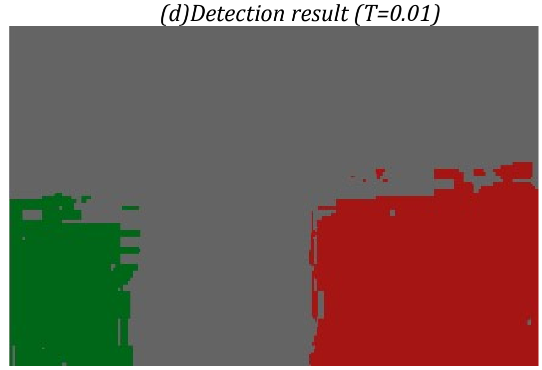
(b) Input image



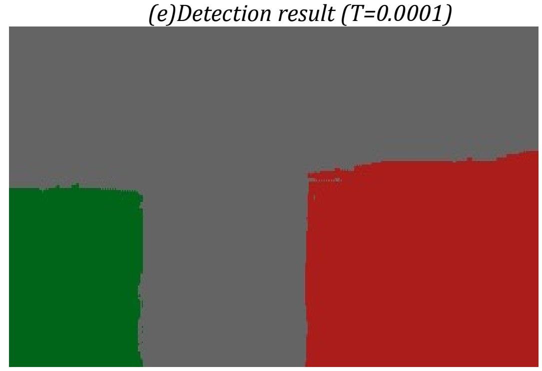
(c) Detection result (T=0.1)



(d)Detection result (T=0.01)



(e)Detection result (T=0.0001)



(f) Detection result (T=0.000000001)

Figure 2: Red and Green Color Detection1

Figure 3(a) is an input image which has 3 colors like Figure 2(b), but it includes dark red color pixels at the upper right region. Figure 3(b) shows that it is not detected when we use Figure 2(a) as a reference image. With the addition of a dark red

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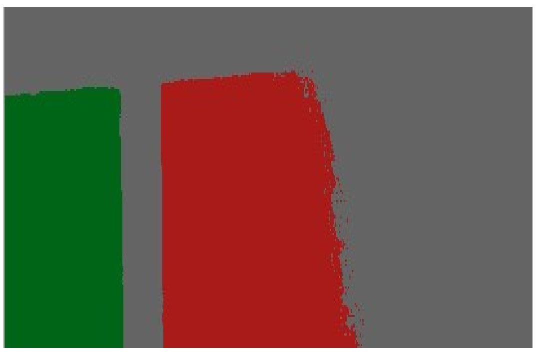
color region in the reference image, the trouble can be solved.

(a) Input image



(b) *Detection result*

Figure 3: Red and Green Color Detection2

Figure 4(a) is a reference image with a darker red color region. Equation (10) shows the calculated GMM parameters. By using Figure 4(a), we can detect the whole red color region as Figure 4(b).

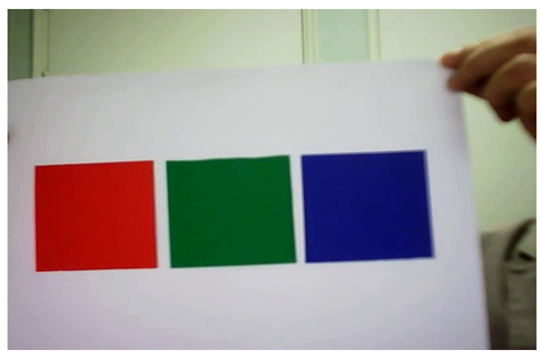
$$w_1 = 0.4044586 \tag{10}$$
$$u_1 = [197.83 \;\; 103.31]$$
$$\Sigma_1 = \begin{bmatrix} 27.3158569 & -9.34145239 \\ -9.34145239 & 3.46817751 \end{bmatrix}$$
$$w_2 = 0.5955414$$
$$u_2 = [83.70 \;\; 105.91]$$
$$\Sigma_2 = \begin{bmatrix} 0.377196412 & -0.0121275719 \\ -0.0121275719 & 0.185260613 \end{bmatrix}$$

(a) Reference image

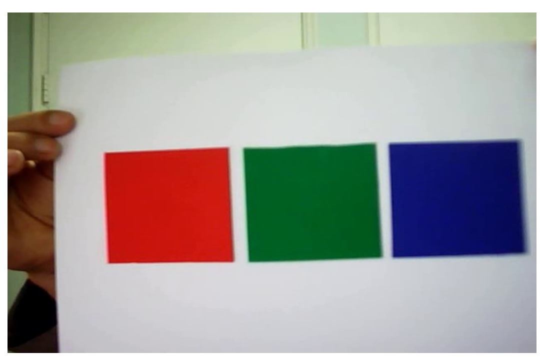
(b) Detection Result

Figure 4: Red and Green Color Detection3

Figure 5 shows input video frames at time t=10, 80, 200, 300, and 450. Figure 6 shows color detection results at the input frames in Figure 5 by using Figure 4(a) as a reference image. We can only detect the red and green color regions of interest in input video frames, but not detect the blue, skin colors and background colors.



(a) t=10



(b) t = 80

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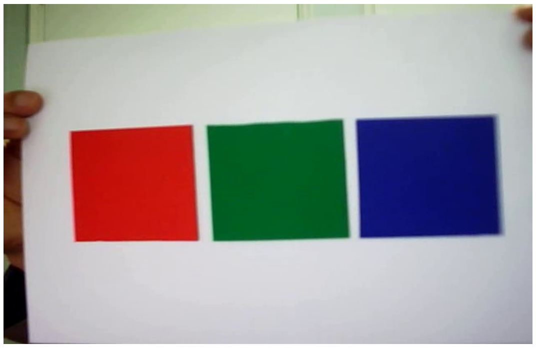
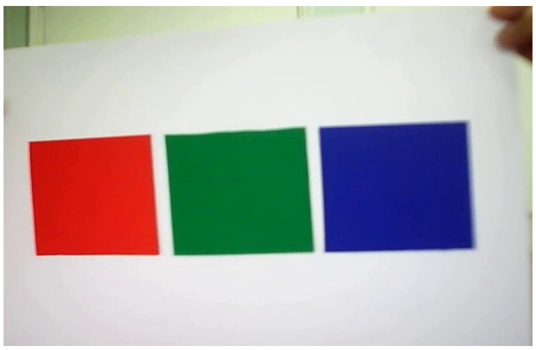
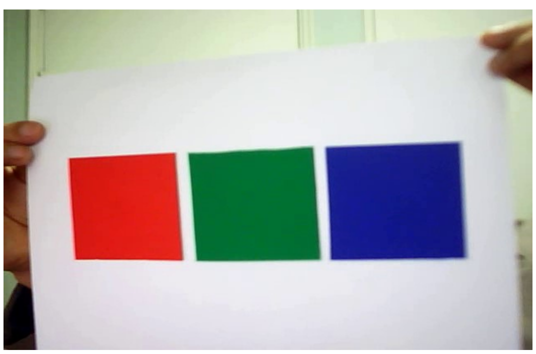


(c) t = 200



(d) t = 300

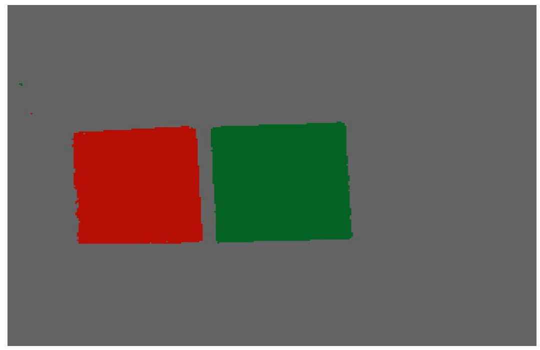


(e) t = 450

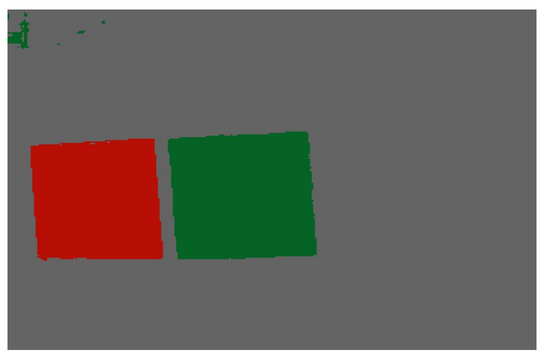
Figure 5: Input frames in a video

(a) t = 10

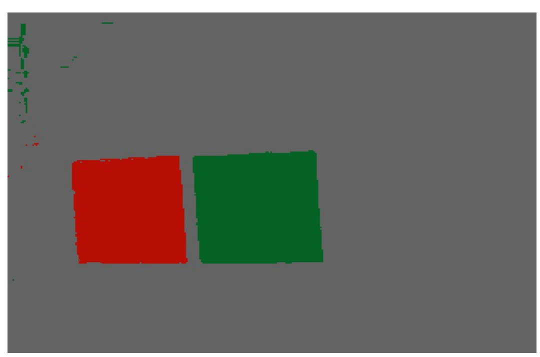
(b) t = 80



(c) t = 200



(d) t = 300



(e) t = 450

Figure 6: Red and Green Color Detection in a video

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5. CONCLUSIONS AND FUTURE WORK

In this paper, we propose a simple color detection method which is based on Gaussian mixture model. We estimate GMM parameters in a reference image including colors of interest and classify pixels in an input image into the color regions of interest by the posterior probability of the Gaussian distributions. Because our work has pixel-wise classification step, it cannot be processed in real-time in a video without parallel programming by using GPUs. In future work, our proposed color detection technique is going to be applied into the other color models like HSV, YIQ, and LAB. It can be applied to n-dimensional feature vector for estimating n-dimensional GMM parameters, and also to estimate distributions in a reference image, K-means clustering can be used. It has the advantage of effectively detecting and segmenting the color regions of interest which are given by user in images and videos.

6. ACKNOWLEDGMENTS

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