Unsupervised approach to color video thresholding

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Abstract. Thresholding of video images is a great challenge because of their low spatial resolution and complex background. We investigate the issue of thresholding these images by reducing the number of colors to improve automated text detection and recognition. We develop an unsupervised approach to video images, which can be considered as an RGB color thresholding method. It applies a gray-level thresholding method to a video image in the (R, G, B) color space to produce a single threshold value for each domain. The three (R, G, B)-generated values will be subsequently processed by an effective unsupervised clustering algorithm that is based on a between-class/within-class criterion suggested by Otsu's method. Since thresholding methods designed for document images may not work effectively for video images in many applications, our proposed RGB color thresholding method has shown to be particularly effective in improvement on text detection and recognition, because it can reduce the background complexity while retaining the important text character pixels. Experiments also show that thresholding video images is far more difficult than thresholding document images, and the RGB color thresholding presented performs significantly better than simple histogram-based methods, which generally do not produce satisfactory results.
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1 Introduction

Information retrieval from video images has become an increasingly important research area in recent years. The rapid growth of digitized video collections is due to the widespread use of digital cameras and video recorders combined with inexpensive disk storage technology. Textual information contained in video images can provide one of the most useful keys for successful information indexing and retrieval. Keyword searches for text of interest within video images can provide additional capabilities to the search engines. In video images, text characters generally have much lower resolution and dimmer intensity than document characters. In addition, videotext characters may also have various colors, sizes, and orientations within the same images. Furthermore, the video background is generally much more complex than that of document images. A combination of this complex background and a large variety of low-quality characters cause thresholding algorithms designed for document image processing to perform poorly on video images.[1–6] We investigate this issue and develop an RGB-based approach that thresholds a video image in the color domain and fuses the obtained threshold values into a set of multiple threshold values via a clustering process. These values are then used to segment text characters from the video image background.

There are many color segmentation techniques reported in the literature,[1–3,5–26] such as texture analysis,[11,15,20,23] histogram thresholding or clustering,[3–6,8,9,19] edge detection,[7] region split and merging,[13,18] and feature analysis.[1,13,16] Histogram thresholding is probably one of the most widely used techniques.[8,27] These segmentation methods basically perform partitions of an image into constituent parts or objects. However, for our applications in text detection and recognition, the only regions of interest are those that may contain potential text, and these regions can be more effectively segmented by thresholding rather than segmentation. Therefore, this work primarily investigates an application of color image thresholding to text detection and recognition in video images.

A general approach to color image thresholding is to transfer a color image to a monochrome image, such as the hue-saturation-intensity (HSI) model[4–6] that transfers a color image into an intensity image. Then, various grayscale thresholding methods can be applied to the monochrome image.[4–6,8] Unfortunately, such an approach encounters a problem, since the color information is decoupled during the color-to-monochrome image conversion. In many cases, the color information proves to be useful in thresholding. As an example,[3] Fig. 1(a) shows an original color image that has pure blue background and pure red text characters with the same grayscale. Figure 1(b) shows an HSI-converted grayscale intensity image that has only one gray level. As we can see in Fig. 1(b), the text characters disappeared because these text characters can be only recognized by their red color in Fig. 1(a), not by their

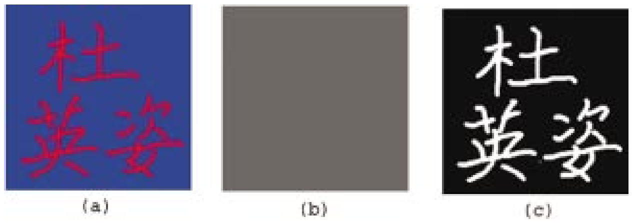

Fig. 1 An example of color image thresholding using HSI: (a) color image, (b) HSI conversion, and (c) desired result.

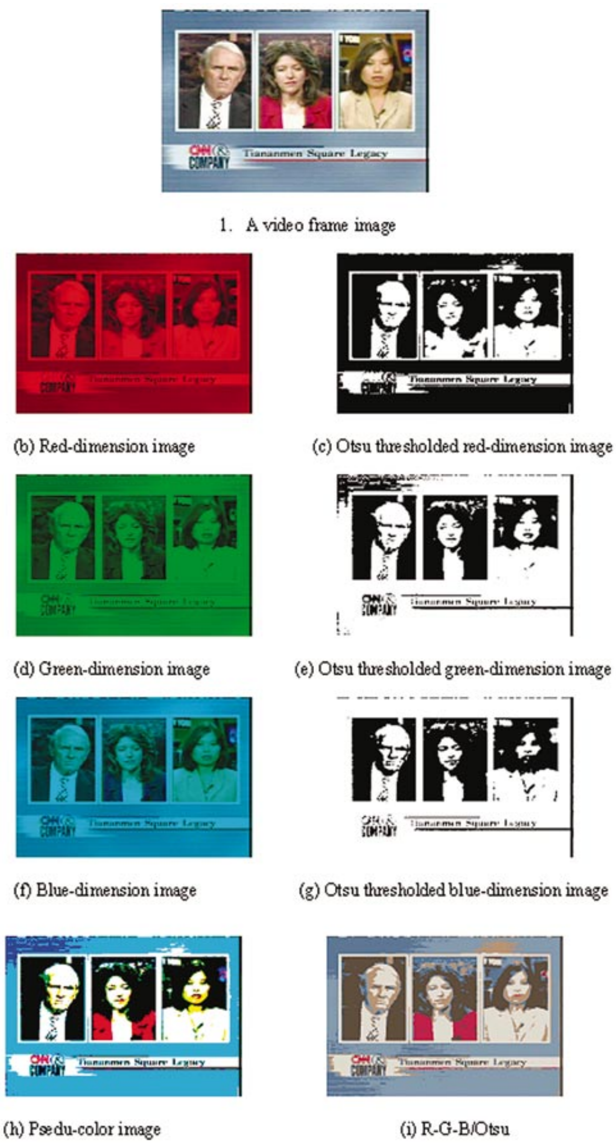

Fig. 2 Step-by-step implementation of RGB color thresholding method: (a) a video frame image, (b) red-dimension image, (c) Otsu thresholded red-dimension image, (d) green-dimension image, (e) Otsu thresholded green-dimension image, (f) blue-dimension image, (g) Otsu thresholded blue-dimension image, (h) pseudo-color image, and (i) RGB/Otsu.

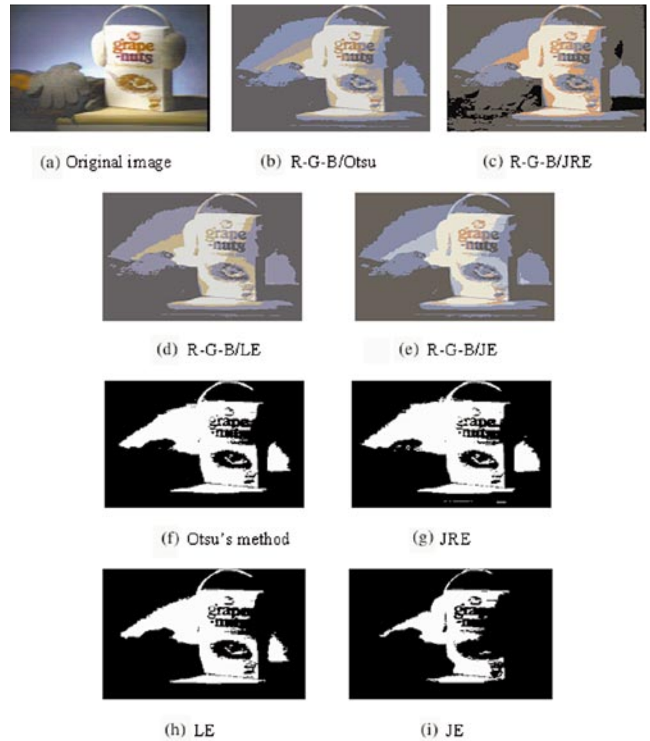

Fig. 3 A TV commercial: (a) original, (b) RGB/Otsu, (c) RGB/JRE, (d) RGB/LE, (e) RGB/JE, (f) Otsu's method, (g) JRE, (h) LE, and (i) JE.

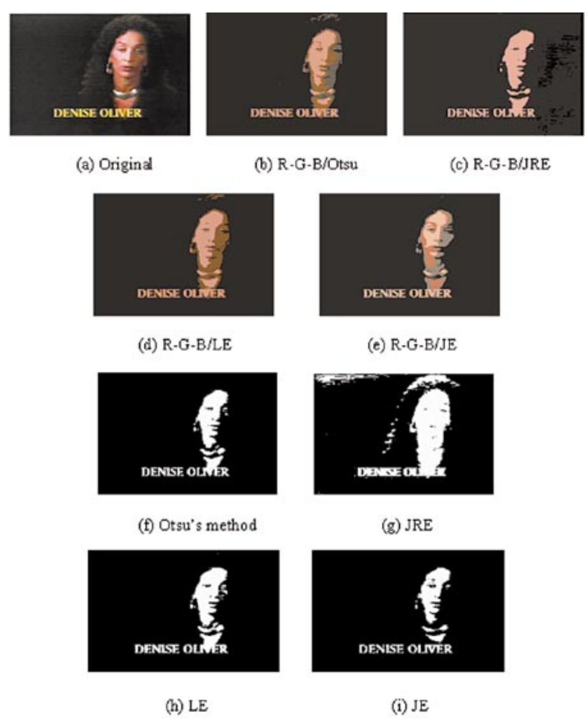

Fig. 4 A woman with the name Denise Oliver: (a) original, (b) RGB/Otsu, (c) RGB/JRE, (d) RGB/LE, (e) RGB/JE, (f) Otsu's method, (g) JRE, (h) LE, and (i) JE.

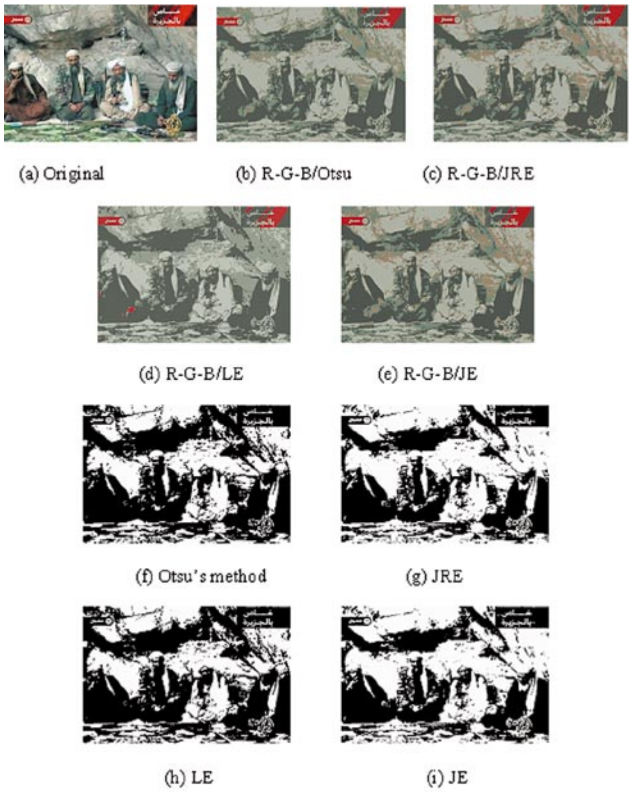

Fig. 5 A newscast video image: (a) original, (b) RGB/Otsu, (c) RGB/JRE, (d) RGB/LE, (e) RGB/JE, (f) Otsu's method, (g) JRE, (h) LE, and (i) JE.

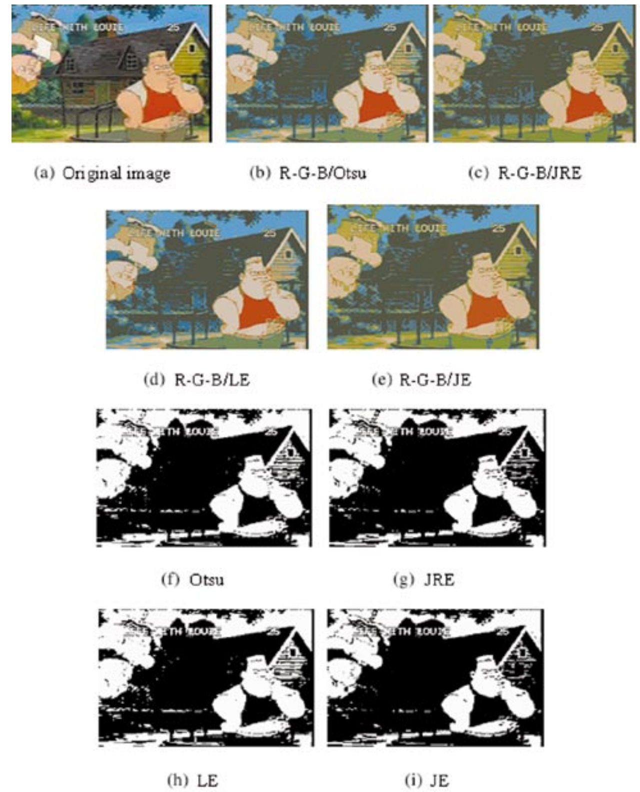

Fig. 6 A cartoon scene: (a) original, (b) RGB/Otsu, (c) RGB/JRE, (d) RGB/LE, (e) RGB/JE, (f) Otsu's method, (g) JRE, (h) LE, and (i) JE.

Fig. 7 A countryside scene: (a) original, (b) RGB/Otsu, (c) RGB/JRE, (d) RGB/LE, (e) RGB/JE, (f) Otsu's method, (g) JRE, (h) LE, and (i) JE.

grayscale in Fig. 1(b). Figure 1(c) shows the desired thresholded result, which extracts the red text characters from the blue background. This simple experiment demonstrates a necessity of inclusion of color information in image thresholding. A 3-D color histogram[19] may be a solution. However, it requires tremendous time and memory to generate a 3-D color histogram. In addition, more time and memory is further required for image manipulation.

In this work, a novel approach is proposed, called an RGB-based thresholding, which can be used for thresholding video and other color images. It first obtains threshold values from each of the R,G,B color domains by a gray-level thresholding method, then implements an unsupervised within-class/between-class clustering process to fuse these R,G,B threshold values to produce a set of multiple thresholds that can extract text effectively while retaining original colors in the image background. Our proposed unsupervised clustering algorithm is derived from the concept of within-class and between-class variances as suggested by Otsu.[28] One major advantage of this algorithm is that it does not need to know how many classes are required to be clustered in advance, as is required for most clustering processes. The algorithm is automatically terminated once the within-class variance is less than the between-class variance for each clustered class. Additionally, the number of classes to be clustered is bounded above by $2^3=8$. Surprisingly, as demonstrated in our experiments, this simple multithresholding method performs very well in text detection and extraction in various video images.

The remainder of this work is organized as follows. Section 2 briefly reviews Otsu's method. Section 3 develops an RGB thresholding method for video images. Section 4 conducts a series of experiments to demonstrate the effectiveness of the proposed RGB thresholding method in a wide variety of video images. Finally, Sec. 5 concludes some remarks.

2 Otsu's Method

Otsu's method[28] is one of the most widely used thresholding techniques in image analysis, which has shown great success in image enhancement and segmentation. Suppose that $\{p_i\}_{i=0}^{L}$ is the gray-level image histogram of an image, and t is the selected threshold gray-level value. We can then calculate the probabilities of background and foreground of the t-thresholded image by

$$P_B^t=\sum_{i=0}^{t} p_i \quad \text{and} \quad P_F^t=1-P_B^t=\sum_{i=t+1}^{L-1} p_i . \tag{1}$$

By virtue of Eq. (1), the means and variances associated with the background and the foreground can be further calculated by

$$\mu_B^t=(1/P_B^t)\sum_{i=0}^{t} ip_i$$

and

$$\mu_F^t=(1/P_F^t)\sum_{i=t+1}^{L-1} ip_i , \tag{2}$$

$$\text{var}_B^t=(1/P_B^t)\sum_{i=0}^{t} (i-\mu_B^t)^2 p_i$$

and

$$\text{var}_F^t=(1/P_F^t)\sum_{i=t+1}^{L-1} (i-\mu_F^t)^2 p_i , \tag{3}$$

$$\begin{aligned}\text{var}_{\text{between-class}}^t&=P_B^t(\mu_B^t-\mu)^2+P_F^t(\mu_F^t-\mu)^2\\&=P_B^tP_F^t(\mu_B^t-\mu_F^t)^2,\end{aligned} \tag{4}$$

where $\mu=\sum_{i=0}^{L-1} ip_i$ is the global mean of the image and

$$\text{var}_{\text{within-class}}^t=P_B^t\text{var}_B^t+P_F^t\text{var}_F^t . \tag{5}$$

A threshold value t_{Otsu} developed by Otsu is the one that maximizes $\text{var}_{\text{between-class}}^t$, or equivalently minimizes $\text{var}_{\text{within-class}}^t$, i.e.,

$$\begin{aligned}t_{\text{Otsu}}&=\arg\{\max_{1\le t\le L}(\text{var}_{\text{between-class}}^t)\}\\&=\arg\{\min_{1\le t\le L}(\text{var}_{\text{within-class}}^t)\}.\end{aligned} \tag{6}$$

3 Unsupervised RGB Thresholding Method

Color images are composed of 3-D information commonly represented by red, green, and blue. Our proposed RGB thresholding method first applies a gray-level thresholding method to each of the R,G,B color domains, respectively. A number of different gray-level thresholding methods can be used for this purpose, including Otsu's method,[28] or a 2-D thresholding method such as an entropy-based method[29] or a relative entropy method.[4–6,30] The selection of an appropriate gray-level thresholding method can be based on the image properties and applications. In this work, Otsu's method is used for the following two reasons. One is that it has been shown to be an effective 1-D gray-level thresholding method in most images. Another is that the proposed unsupervised cluster algorithm is also based on the criterion of within-class/between-class variance used in Otsu's method.

Assume that the threshold values obtained for each of three colors, red (r), green (g), and blue (b) are specified by t_r, t_g, and t_b, respectively, via Eq. (6). Let each pixel in a video image be denoted by $p_{i,j}=(r_{i,j},g_{i,j},b_{i,j})^T$ with (i,j) being the spatial coordinate of the pixel. Using t_r, t_g, t_b as preliminary threshold values in each color domain, the pixel $p_{i,j}=(r_{i,j},g_{i,j},b_{i,j})^T$ can be thresholded as $\tilde{p}_{i,j}=(\tilde{r}_{i,j},\tilde{g}_{i,j},\tilde{b}_{i,j})^T$, according to

$$\tilde{r}_{i,j}=\begin{cases}1 & r_{i,j}>t_r\\0 & r_{i,j}\le t_r\end{cases}, \quad \tilde{g}_{i,j}=\begin{cases}1 & g_{i,j}>t_g\\0 & g_{i,j}\le t_g\end{cases},$$

$$\tilde{b}_{i,j}=\begin{cases}1 & b_{i,j}>t_b\\0 & b_{i,j}\le t_b\end{cases}. \tag{7}$$

As a result, each (r,g,b)-color pixel in a video image can be encoded by a 3-bit binary codeword (c_1,c_2,c_3), where c_i for $1\leqslant i\leqslant 3$ is a binary value taking either 0 or 1. Then, we cluster all image pixels into eight classes $\{C_k\}_{k=1}^{8}$ according to their associated codewords, where each codeword represents a clustered class. For example, all pixels encoded by (1,0,0) will be clustered into one class.

Next, the mean of each clustered class, say the k'th class C_k, denoted by $\mu_k=(r_k,g_k,b_k)^T$ is calculated by

$$r_k=\sum_{r_{i,j}\in C_k} r_{i,j} \Big/ \sum_{r_{i,j}\in C_k} 1,\ \ g_k=\sum_{g_{i,j}\in C_k} g_{i,j} \Big/ \sum_{g_{i,j}\in C_k} 1,$$

$$b_k=\sum_{b_{i,j}\in C_k} b_{i,j} \Big/ \sum_{b_{i,j}\in C_k} 1. \tag{8}$$

Following the definitions of within-class and between-class variances given in Otsu's method,[28] we further calculate the within-class variance σ_k for each class of $\{C_k\}_{k=1}^{8}$ as

$$\sigma_k=\frac{1}{N_k}\left\{\sum_{i,j\in C_k}[(r_{i,j}-r_k)^2+(g_{i,j}-g_k)^2+(b_{i,j}-b_k)^2]\right\}^{1/2}, \tag{9}$$

where N_k is the number of pixels in class C_k. The between-class variance σ_{kj} between two classes C_k and C_j with $k\neq j$ can be calculated as:

$$\sigma_{ij}=\sqrt{(r_k-r_j)^2+(g_k-g_j)^2+(b_k-b_j)^2)^{1/2}}, \tag{10}$$

where $(r_k,\ g_k,\ b_k)$, $(r_j,\ g_j,\ b_j)$ are defined by Eq. (8) and mean values of classes C_k and C_j correspond to the R,G,B domains, respectively.

Now, we use the within-class variances σ_k, σ_j, and the between-class variance σ_{kj} obtained earlier as criteria to reshuffle pixels to form a new set of clusters. If two classes C_k and C_j for $k\neq j$ with either $\sigma_k\geqslant\sigma_{kj}$ or $\sigma_j\geqslant\sigma_{kj}$, these two classes must be merged to one class. This is because the between-class variance between two classes σ_{kj} must be greater than their individual with-in class variances σ_k and σ_j. This reclustering process is repeated until all the between-class variances are greater than their corresponding within-class variances, in which case no classes will be reshuffled.

Figure 2 shows a video broadcast news example to demonstrate a step-by-step implementation of our proposed unsupervised RGB thresholding method. Figure 2(a) is the original color video image. Figures 2(b), 2(d), and 2(f) are red, green, and blue images of the color image in Fig. 2(a), respectively. Figures 2(c), 2(e), and 2(g) are their respective thresholded images with thresholds given by 149, 115, and 115, respectively. Figure 2(h) is a pseudo-colored image to show the (149,115,115)-thresholded color image with eight different colors before a reclustering process took place. Figure 2(i) is the (149,115,115)-thresholded color image with six different colors after the image in Fig. 2(h) was reclustered.

This idea is very similar to that of ISODATA,[31] except for three subtle differences. One is that the criteria used in our process are not nearest neighboring rule (NNR) as commonly used in ISODATA. A second difference is that if class A is merged with class B, and class B is also merged to a third, class C, then these three classes, A, B, and C, must be merged into one class. As a result, the number of classes is therefore reduced. This yields a third difference, which is that there is no need of predetermining the number of classes to be clustered as required by ISODATA. The details of implementing our proposed RGB thresholding method can be summarized in the following step-by-step procedure.

3.1 *RGB Color Thresholding Algorithm*

1. Use a gray-level thresholding method, such as Otsu's method, to threshold video images in three color domains individually. Let t_r, t_g, and t_b denote the resulting threshold values.
2. Use Eq. (7) to encode all the (RGB)-pixel vectors into 3-bit binary codewords. All pixels with the same codeword will be clustered into a single class.
3. Use Eq. (8) to calculate the mean for each class, i.e., the gray-level intensity average of pixels in each class along the R,G,B color domains.
4. Use Eq. (9) to calculate the within-class variance and the between-class variance for each class.
5. For any two classes C_k and C_j with $k\neq j$, compare the within-class variance σ_k and σ_j against the between-class variance σ_{kj} to see if $\sigma_k\geqslant\sigma_{kj}$ or $\sigma_j\geqslant\sigma_{kj}$. If no, terminate the reclustering process. Go to step 7. Otherwise, continue.
6. Merge the classes C_k and C_j into one class and go to step 3. It should be noted that if one of the classes, C_k and C_j, is merged with a third class, C_l, these three classes C_k, C_j, and C_l must be merged into one class. Go to step 3.
7. At this step, no pixel vectors will be reshuffled and all the (RGB)-pixel vectors in each of the resulting classes will be assigned by the same color as the mean pixel vector of that particular class. In other words, the color of the centroid of a class will be assigned to all the (RGB)-pixel vectors in that particular class.

4 Experimental Results

In this section, we conduct a series of experiments to demonstrate the effectiveness of our proposed RGB thresholding method. Two observations were witnessed and interesting. First, simple global gray-level thresholding methods did not generally work for color thresholding. Second, the proposed RGB thresholding approach coupled with simple gray-level thresholding methods could significantly improve results, specifically in text detection. Four gray-level thresholding methods were used in the RGB thresholding for comparison, which were Otsu's method,[28] Pal and Pal's local entropy (LE) and joint entropy (JE),[29] and the joint relative entropy (JRE) method.[30] The selection of Otsu's method is based on: 1. that the proposed clustering process

Table 1 Threshold values generated by the Otsu, JRE, LE, and JE methods.

	RGB/Otsu (R,G,B)	RGB/JRE (R,G,B)	RGB/LE (R,G,B)	RGB/JE (R,G,B)
TV commercial	(141,138,122)	(188,14,121)	(140,133,150)	(185,167,121)
Woman	(111,89,81)	(4,6,94)	(74,82,66)	(155,130,95)
Newscast	(115,119,111)	(116,115,108)	(135,132,135)	(116,117,106)
Cartoon scene	(127,111,105)	(131,117,93)	(119,109,129)	(128,124,99)
Countryside scene	(95,100,106)	(10,11,86)	(161,81,76)	(94,92,85)

adopts the same criterion used in Otsu's method, i.e., within-class and between-class variances; and 2. that Otsu's method is a widely used thresholding technique, which has been shown to be very effective for gray-level images. On the other hand, entropy-based thresholding methods have shown to be promising and effective in image thresholding. In particular, a recent report in Ref. 5 showed that JRE was effective in color thresholding when a single threshold value was used. These four methods were implemented in step 1 in the RGB thresholding method, referred to as RGB/Otsu, RGB/LE, RGB/JE and RGB/JRE, respectively. Their results were then compared to the results obtained by single gray-level thresholding methods.

1209 single-frame video images were used for the experiments. These 1209 video images are from the University of Maryland, College Park database, which covers a broad range of different kinds of video images from different TV channels: TV commercial video, cartoons, news, soaps, and TV shows. No conclusion can be drawn on which one RGB color thresholding method performs better than the others. Nevertheless, in all the cases, the single threshold gray-level thresholding methods, Otsu's method, LE, JE, and JRE did not perform well compared to those using RGB thresholding. Due to limited space, we only include five experiments in this work, which are representative for demonstrating the superior performance of our proposed RGB color thresholding approach. Figures 3–7 show the results produced by RGB/Otsu, RGB/LE, RGB/JE, and RGB/JRE, where we can see that RGB/Otsu, RGB/LE, RGB/JE, and RGB/JRE performed slightly differently, but all of them performed substantially better than did the single gray-level thresholded methods. Table 1 tabulates the threshold values generated by the Otsu, JRE, LE, and JE methods along each of the R, G, B color domains for comparison. As shown in Table 1, all the threshold values generated by the four methods are very different for five tested scenes in a wide range. Table 2 also lists the number of colors required for each of the four RGB color thresholding methods for video image segmentation resulting from the proposed between-class/within-class clustering process in the RGB color thresholding algorithm. Each class requires one color for all the (RGB)-pixel vectors in that class. The color of each class was chosen to be the color of the centroid of that particular class. Figure 3 is interesting and deserves more explanation. It is a TV commercial where the scene has a box with the text "grape-nuts" on the front cover and a glove next to the box. All four of the RGB color thresholded methods successfully extracted the text with two subtle differences, the glove and rainbow background behind the box. Except for the fact that the RGB/JRE extracted most of the glove including the finger portion, the other three could not segment the glove from the background, as its gray color is close to the background. As for the rainbow background, RGB/Otsu pulled it out with three colors, compared to two colors from the other three RGB color thresholding results. In terms of numbers of colors used, the RGB/Otsu is the best because it only used three colors compared to four colors required by the other three. Nevertheless, it seemed that RGB/JRE produced the best result in the sense that it extracted the text and glove that the others could not. Figure 4 shows a woman with name "Denise Oliver" in a black background. The result produced by the RGB/JE seemed best, because the extracted text had better contrast and the shadow under the neck was also shown in its thresholded result. As for single gray-level thresholding methods, JRE performed the worst, while the other three performed very similarly. Figure 5 shows a very busy newscast video image, where all four RGB color thresholding methods performed very closely. Figure 6 is a cartoon scene, where there are two cartoon characters with text "Life with Louie 25" on the top. All four RGB color thresholding methods segmented the text and the two cartoon characters from the background very well, and there was no visible difference in their thresholded results. Similarly, the results produced by the four single gray-level thresholding methods were also very close, but certainly were not good. Figure 7 is a countryside scene with the text "Hallmark Hall of Fame" on the left corner. The RGB/LE and RGB/JE seemed to perform slightly better than RGB/Ostu and RGB/JRE in terms of contrast in the image background and the text "Hall of Fame," which was extracted more visibly. For the results produced by the four single gray-level thresholding methods, they were all similar, where the text was barely extracted.

These experiments demonstrated that the proposed RGB color thresholding is promising in the segmentation of color

Table 2 Number of colors required for four RGB color thresholding methods.

	RGB/Otsu	RGB/JRE	RGB/LE	RGB/JE
TV commercial	4	5	5	5
Woman	4	3	4	4
Newscast	5	5	5	5
Cartoon scene	7	7	7	7
Countryside scene	4	3	4	4

images, which generally cannot be accomplished by a single gray-level thresholding method. Additionally, these experiments also showed that the proposed RGB color thresholding could extract not only scene text in Fig. 3, but also superimposed text in Figs. 4–7.

5 Conclusions

An RGB color thresholding approach is developed for segmentation of video images. It is a simple multithreshold segmentation method that implements a gray-level thresholding method in each of the R, G, B domains, then uses the generated threshold values as a base to produce a set of desired multiple threshold values for video image segmentation by means of an unsupervised clustering process. Several contributions are made. One is that it extends single gray-level thresholding techniques to multilevel thresholding for video images. Another is that the designed clustering process in the RGB color thresholding is a new approach that uses an unsupervised between-class/within-class-based algorithm to fuse different threshold values obtained from the RGB color domain. A third contribution is that the clustering process can be implemented in conjunction with any gray-level thresholding technique to adapt to various applications. The experiments demonstrate that the proposed RGB color thresholding method performs significantly better than single gray-level thresholding methods. Also shown in the experimental results, the performance of the proposed RGB color thresholding method is very robust to the selection of the single gray-level thresholding method that is used to produce threshold values in the RGB domain. This advantage is very important, since we do not have to specify a particular single gray-level thresholding method in the RGB color thresholding. It should be noted that in the case that other color spaces, such as CIE (Commission Internationale de l'Eclairage), YUV (Y: luminance, U: Red-Y, V: Blue-Y), and YIQ (Y: luminance, $I=0.74V-0.27U$, $Z=0.48V+0.41U$) are used, they can be first transferred to the RGB color space in the same manner as was done for the HSI color space, and then our proposed RGB color thresholding method follows afterward.

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