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Color image Segmentation using automatic thresholding techniques

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ABSTRACT

In this paper, entropy and between-class variance based thresholding methods for color images segmentation are studied. The maximization of the between-class variance (MVI) and the entropy (ME) have been used as a criterion functions to determine an optimal threshold to segment images into nearly homogenous regions.

Segmentation results from the two methods are validated and the segmentation sensitivity for the test data available is evaluated, and a comparative study between these methods in different color spaces is presented. The experimental results demonstrate the superiority of the MVI method for color image segmentation.

Index Terms—*Entropy, Between-class, Automatic thresholding, Color image, Segmentation, HSI color space.*

1. INTRODUCTION

Image segmentation is very essential and critical to image processing and pattern recognition. It is one of the most difficult tasks in image processing. The goal of image segmentation is the partition of an image into a set of disjoint areas with uniform and homogeneous attributes such as intensity, color, tone or texture, etc.

In this framework, color image segmentation has wide applications in many areas, and many different techniques have been developed. Until now there is no general technique that can solve all the different image segmentation types.

Thresholding is a technique frequently applied to image segmentation. However, it requires an adequate threshold values to divide an image into different regions. This technique is widely used in many image processing applications such as: detection of video change [1] medical image processing [2], optical character recognition [3], etc.

Several algorithms have been proposed in literatures for color image segmentation that have addressed the issue of histogram thresholding.

In this context, cheng et al. [4] [5] have extended the general idea of a histogram to homogeneity domain. In the first step, the homogeneity is calculated for an image pixel where both local and global information are considered. In the second step, a hierarchical histogram analysis method based on homogeneity and color features is employed to determine the uniform regions. Finally, a region merging process is employed to ovoid aver-segmentation.

Also, the Fuzzy C-means (FCM) [6], an unsupervised clustering algorithm, has been applied successfully to a number of clustering problems. The FCM method of image segmentation identified the uniform region by minimizing the objective function for the partition of data set. However this method becomes very time-consuming due to the fact a large number of iterations are required for computing the matrix memberships. To greatly improve the efficiency of FCM algorithm, S. B. Chaabane et al. [6] have proposed a segmentation algorithm for color images based on the thresholding and the Fuzzy C-means techniques. The thresolding technique is used to segment coarsely the image, while the FCM is used to assigns the pixels, which remain unclassified after the threshold operation, to the closest class.

In fact, several algorithms have been proposed in literatures that have addressed the issue of histogram thresholding [7] [8] [9]. The most widely used clustering method is the Otsu's method [10].

Otsu's method is one of the better ways of image segmentation, which selects a global threshold value by minimizing the variance inter-classes in the grey level image. The major problem of this method resides in the determination of the optimal thresholds, especially if there is a large class number required in the image. However, several methods have been proposed to greatly improve the efficiency of Otsu's method. Recently, D. Y. Huang et al. [11] have presented a new fast algorithm called the two stage multithreshold Otsu method. This algorithm is used to reduce the large number of iterations required by Otsu's method for computing the cumulative probability and the mean of a class.

To effectively show the efficiency of determining the threshold of separation, this paper presents a comparative study between clustering and entropy based thresholding methods applied to color images segmentation.

The paper is organized as follows. The entropy and the between-class variance based thresholding methods are formulated in Section 2. Also, some color representations and their advantages/disadvantages are reviewed in this section.

The experimental results are discussed in section 3, and the concluding remarks of this work are given in section 4.

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2. HISTOGRAM THRESHOLDING AND COLOR SPACE CLUSTERING

Generally, color segmentation approaches are based on monochrome segmentation approaches operating in different color spaces. In this section, we discuss the thresholding methods for image segmentation: entropy based thresholding method and the between-class based thresholding method. Also, we reviewed some color representations and their advantages and disadvantages.

2.1 histogram thresholding

Histogram thresholding [12], is one of the widely used techniques for the gray level image segmentation. The main objective is to determine an efficient threshold (for bi-level thresholding) or several thresholds (for multi-level thresholding). In the case where the histogram contains a distinct valley, the threshold determination problem is simple and will be a bi-level thresholding. Consequently, the image can be segmented by this threshold value.
This can facilitate to generate a binary image where all pixels having grey levels lower than the threshold are assigned to one set or class and pixels having gray levels higher than the threshold are assigned to another set or class. However the problem gets more and more complex when we extend the segmentation to a multi-level thresholding and the valleys that exist in the histogram are not distinct. Then the image segmentation problem becomes a multi-class classification problem.
As for color images, the situation is different due to the multi-features. Since the color information is represented by the three component images R, G and B or some linear/nonlinear transformation of RGB, representing the histogram of a color image in a three dimensional (3D) arrays and selecting threshold in the histogram is not a trivial job. One way to solve this problem is to develop efficient methods for storing and processing the information of the image in the 3D color space.
In our application, we propose to use the automatic thresholding techniques for color image segmentation. These methods are based, respectively, on the maximum of the between-class variance and the entropy. Hence, this paper is devoted to selecting a threshold, applied to color image segmentation, where, we aim at providing a help to the doctor for the follow-up of the diseases of the breast cancer. The objective is to rebuild each cell from the R, G, B, H, S and I components of the original image represented in the RGB and HSI color spaces.

2.1.1. Entropy based thresholding method

This class of algorithms exploits the entropy [13][14], of the distribution of the gray levels in a scene. From a conventional point of view, the entropy is a basic thermodynamic concept that is associated with the order of irreversible processes in the universe. Physically it can be associated with the amount of disorder in a physical system. The maximization of the entropy of the thresholded image is interpreted as indicative of maximum information transfer.
The entropy was first introduced by Boltzmann/Gibbs [13] and formalized by Shannon [15]. He defined an expression for measuring quantitatively the amount of information produced by a process.
The Shannon entropy [15], may be described as:

$$E = \sum_{i=0}^{n_c-1} E(C_i) \qquad (1)$$

Assume that an image can be represented in L gray levels. The number of pixels at level *I* is denoted by *h(i)*. If this image, is divided into two (n_c=2) classes, C_0 et C_1, by a threshold at level t, where class C_0 consists of N_0 gray levels from 0 to t, and class C_1 contains the other gray levels (N_1) with t+1 to L, then the entropy ($E(C_0)$, $E(C_1)$) for classes C_0 and C_1, and the the posterior probability of gray level i in the class C_0 and C_1, respectively, are given by:

$$E(C_0) = -\sum_{i=0}^{s} p(i/C_0^s)\log[p(i/C_0^s)] \qquad (2)$$

$$E(C_1) = -\sum_{i=s+1}^{255} p(i/C_1^s)\log[p(i/C_1^s)] \qquad (3)$$

and

$$p(i/C_0^s) = \frac{h(i)}{N_0} \qquad (4)$$

$$p(i/C_1^s) = \frac{h(i)}{N_1} \qquad (5)$$

The thresholding method selects an optimal threshold that maximizes the entropy in Eq.6.

This class of algorithms exploits the entropy of the distribution of the gray levels in a scene. In fact, the thresholds are determined based on the maximization of the criterion function E. The maximization of the entropy (E) of the thresholded image is interpreted as indicative of maximum information transfer.

The mathematical procedure of the *Entropy based thresholding* process is described in the following steps:

Step 1*: Choose a threshold S between 0 and 255.*

Step 2*: Calculate the total entropy E() of this threshold according to the formula:*

$$E(S) = -\sum_{i=0}^{s} p(i/C_0^s)\log[p(i/C_0^s)] - \sum_{i=s+1}^{255} p(i/C_1^s)\log[p(i/C_1^s)] \qquad (6)$$

Step 3*: Determine the threshold S_0 as:* $E(S_0) = \max(E(s))$

Step 4*: Create the segmented image for S_0.*

2.1.2. Between-class variance based thresholding method

Between-class variance was introduced first by Otsu [10] as a discriminant function to determine an optimum threshold from an image histogram to segment images into nearly homogenous regions.
Assume that an image can be represented in L gray levels (1, 2, . . . , L). The number of pixels at level i is denoted by f_i and N represents the total number of pixels in a given image. For a given gray-level image, the occurrence probability of gray level i is defined as:

$$P_i = \frac{f_i}{N}, \quad P_i \geq 0, \quad \sum_{i=1}^{L} P_i = 1 \tag{7}$$

In the case of single thresholding, the pixels of an image are divided into two classes, C_1 and C_2, by a threshold at level t, where class C_1 consists of gray levels from 0 to t, and class C_2 contains the other gray levels with t+1 to L.
The cumulative probabilities (W_1 and W_2) of the two classes, respectively, are given by:

$$W_1 = \sum_{i=1}^{t} p_i \tag{8}$$

$$W_2 = \sum_{i=t+1}^{L} p_i \tag{9}$$

The mean levels (μ_1 and μ_2) for classes C_1 and C_2 can be computed as:

$$\mu_1 = \sum_{i=1}^{t} \frac{i \cdot p_i}{w_1} \tag{10}$$

$$\mu_2 = \sum_{i=t+1}^{L} \frac{i \cdot p_i}{w_2} \tag{11}$$

Otsu [29] selects an optimal threshold t* that maximizes the between-class variance σ_B^2 in Eq. (6) where μ_T is the mean intensity of the original whole image.

$$t^* = \arg_{1 \leq t < L} \max \left\{ \begin{aligned} \sigma_B^2(t) / \sigma_B^2 = w_1(\mu_1 - \mu_T)^2 \\ + w_2(\mu_2 - \mu_T)^2 \end{aligned} \right\} \tag{12}$$

and

$$\mu_T = \sum_{i=t+1}^{L} i \cdot p_i \tag{13}$$

The Otsu method [10], described here can be easily extended to multilevel thresholding of an image [11].

2.2. Color space

2.2.1. HSI color space

HSI system separates color information of an image from its intensity information. Color information is represented by hue and saturation values, while intensity, which describes the brightness of an image, is determined by the amount of the light. Hue is the most useful attribute in color segmentation since it is less influenced by the nonuniform illumination such as hade, shadow, or reflect lights [16]. Hue can be obtained by a nonlinear transformation from R, G and B color features [16]:

$$Hue = \arctan\left(\frac{\sqrt{3}(G-B)}{(R-G)+(R-B)}\right) \tag{12}$$

Hue represents basic colors, and is determined by the dominant wavelength in the spectral distribution of light wavelengths. It reflects the predominant color of an object and has a great capability in subjective color perception [16].

2.2.2. RGB color space

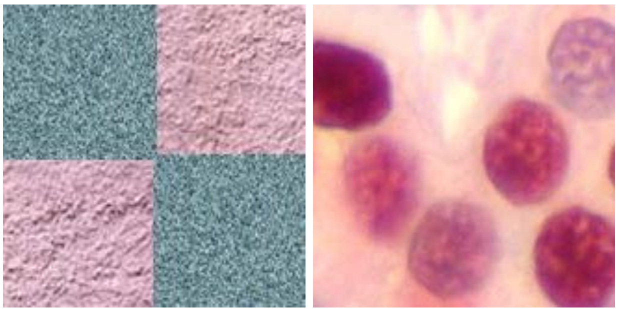
The Red, Green and Blue (RGB) color space is widely used throughout computer graphics [16]. Red, Green, and Blue are three primary additive colors and are represented by a tridimensional coordinate system. The three components can be represented by the brightness values of the scene obtained through three separate filters (red, green, blue filters) based on the following equations:

$$\begin{aligned} R &= \int_\lambda E(\lambda) S_R(\lambda) d\lambda \\ G &= \int_\lambda E(\lambda) S_G(\lambda) d\lambda \\ B &= \int_\lambda E(\lambda) S_B(\lambda) d\lambda \end{aligned} \tag{13}$$

where S_R, S_G, S_B are the color filters on the incoming light or radiance $E(\lambda)$, and λ is the wavelength.

3. EXPERIMENTAL RESULTS AND DISCUSSION

The thresholding methods have been extensively tested on color cells images. Also, a synthetic image dataset is developed and used for numerical evaluation purpose. Some experimental results are shown in Figs. 2-5. We applied the between-class variance and the entropy based thresholding methods to same image, and compared the obtained results with these obtained in each component of the image represented in RGB and HSI color spaces.



(a) (b)

Figure 1. Synthetic image (a) and real medical cells image (b)

The two images shown in Fig.1 were used in order to visually assess the quality of the segmentation results. The synthetic image (Fig. 1(a)) contains 2 areas and can be considered as piecewise constant in most of its areas. Fig. 1(b) shows a real medical cells image, obtained by a coloring himino-histochimy in the Cancer Service, Salah Azaiez Hospital, Bab Saadoun, Tunis, Tunisia.
Fig. 2-5 demonstrates the results of the two thresholding methods. Fig.2 shows the segmentation results based on the between-class variance based thresholding method, applied to red, green and blue components images.

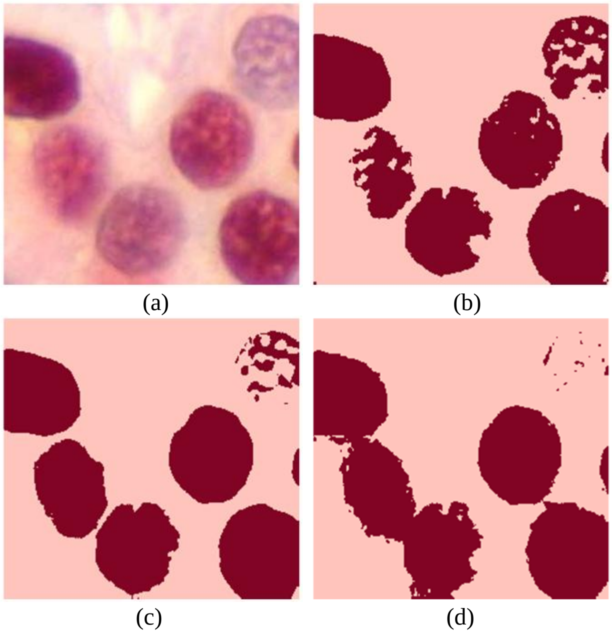


Figure 2. Segmentation results on a color image, (a) Original image (256x256x3) with gray level spread on the range [0,255]. (b) Red resulting image by the between class variance based thresholding (MVI) method. (c) Green resulting image by MVI method, (d) Blue resulting image by MVI method.

In this case, several misclassified pixels are presents in the segmented images. This shows the high correlation of the three components images (R, G and B). Comparing the results, we can find that the cells are much better segmented in Fig. 2(c) than those in Fig. 2(b) and 2(d).
In fact, this demonstrate the necessity of choose the adapted space color and the adapted segmentation technique for a specific application.
For purpose comparison, we apply the entropy based thresholding method (ME) and the between-class variance based thresholding method (MVI) to the same color image (Fig. 1(a)), represented in HSI color space. The experimental results shown in Fig. 3 indicate that the between-class variance based thresholding method, which applied to the Hue color feature, is better than the entropy based thresholding method.
As shown in Fig. 3(d), the two regions (textures) are better recognized by between-class variance based thresholding method.

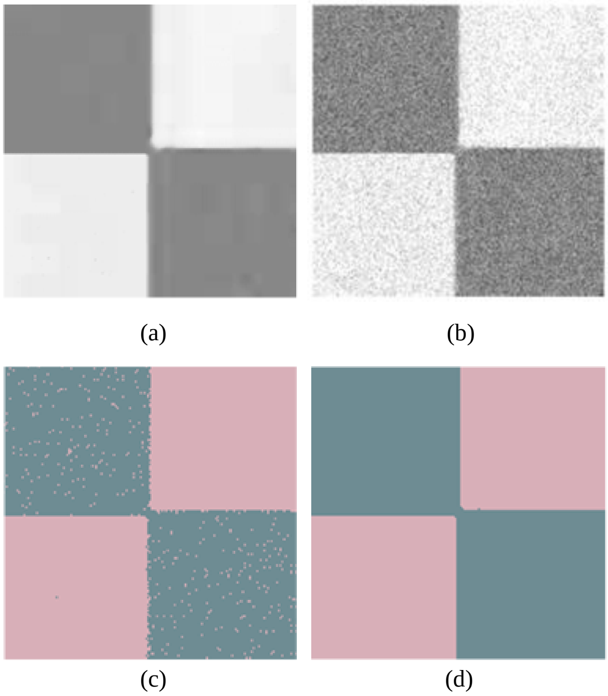


Figure 3. (a) Hue color feature, (b) Hue color feature disturbed with a "Gaussian" noise ($\sigma = 5.10^{-3}$) and with gray level zero to 255 and 2 classes, (b) Hue resulting image by ME method, (d) Hue resulting image by MVI method.

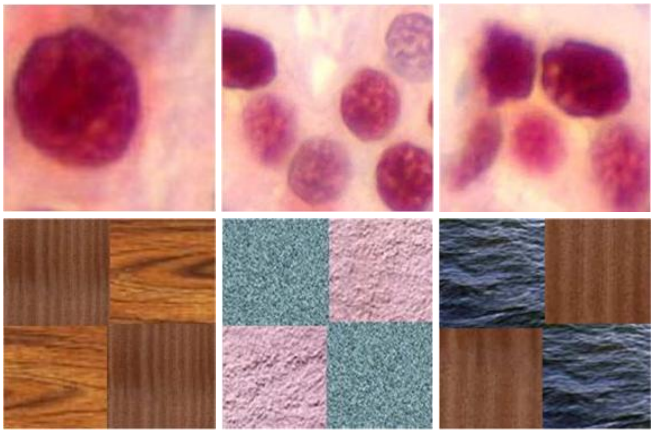


Figure 4. Data set used in the experiment. Six images were selected for a comparison study. The patterns are numbered from 1 to 6, starting at the upper left-hand corner.

The difference can also be observed in Fig. 5. The experimental results are obtained by applying the MVI method to red and hue color feature of Fig. 1(b), respectively.
The cells are misclassified as red during the segmentation using RGB space (Fig. 5(b)). The same cells are segmented correctly using hue (fig. 5(c)). This proves that Hue is less influenced by shadow and highlight in an image. In fact, the difference of the segmentation results is related to the choice of color feature and the segmentation technique.

TABLE I
SEGMENTATION SENSITIVITY FROM MVI METHOD FOR THE DATA SET SHOWN IN FIGURE 4

	MVI					
	H	**S**	**I**	**R**	**G**	**B**
Image 1	91.12	90.47	86.58	79.58	85.52	85.47
Image 2	84.73	81.25	90.52	81.98	84.75	75.45
Image 3	86.45	94.85	96.58	84.74	79.85	69.45
Image 4	95.85	85.45	93.25	78.54	71.52	80.25
Image 5	96.52	84.52	81.45	78.47	71.85	75.24
Image 6	94.52	92.47	90.52	80.47	70.14	69.14

To evaluate the performance of the clustering techniques, this accuracy were recorded. Regarding the accuracy, Tables I and II list the segmentation sensitivity and the correctly and the incorrectly probability detection of the different methods for the data set used in the experiment.
It can be seen from table I that 15.48%, 18.55%, 21.53%, 28.15% and 24.76% of the pixels were incorrectly segmented by the between-class variance based thresholding method, applied to five features (S, I, R, G and B) of Fig. 1(a), respectively, but only 03.48% incorrectly segmented are presented by using the hue color feature.
Comparing Fig. 3(c) and 3(d), we can see that the resulting images from the between-class variance based thresholding method are much clearer where using the hue color feature.

TABLE II
PC AND PF FROM ME AND MVI METHOD FOR THE DATA SET SHOWN IN FIGURE 4

	ME		MVI	
	PF	**PC**	**PF**	**PC**
Image 1	0.3478	0.5486	0.1987	0.6735
Image 2	0.3347	0.5579	0.1513	0.6978
Image 3	0.2945	0.5948	0.1148	0.6453
Image 4	0.2648	0.6978	0.1431	0.7364
Image 5	0.3789	0.6187	0.1385	0.6569
Image 6	0.2678	0.6228	0.1262	0.7192

Two experimental quantitative methods are used in medical images segmentation. They include the segmentation sensitivity, the probability of correctly detection and the probability of the incorrectly detection. These criteria are choosing for the final assessment stage and that were revealed efficient for our application.
The segmentation sensitivity [17] [18], is a valuation principle based on the features of the segmented object. Assume E_f is the labeling of the object in the reference image, and E_s the labeling of the object in the segmented image. In fact, the number of correctly classified pixels (Np_{cc}) is calculated by the comparison between E_f and E_s, and the segmentation sensitivity (Sen%) is defined by :

$$Sens(\%) = \frac{Np_{cc}}{N \times M} \times 100 \qquad (16)$$

with *Sens, Npcc and NxM* correspond, respectively, to the segmentation sensitivity (%), number of correctly classified pixels and dimension of the image.

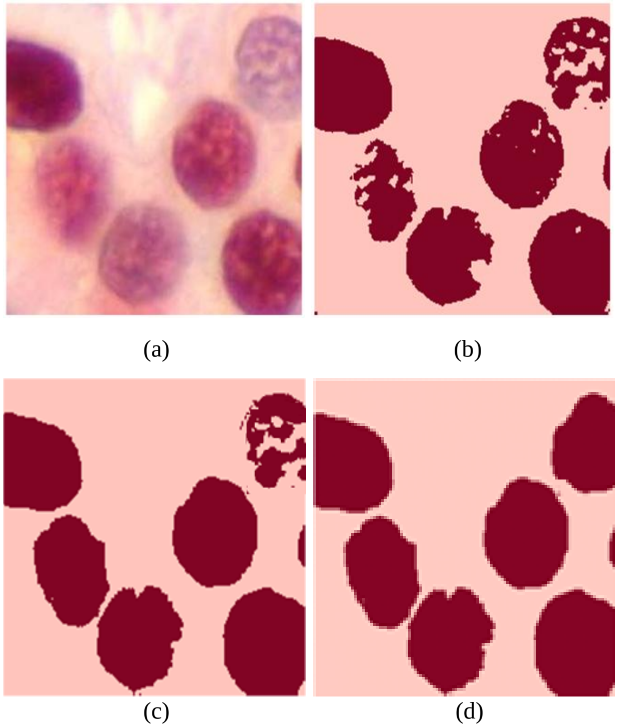


Figure 5. Segmentation results on a color image on a medical image (2 classes, various cells), (a) Original image (256x256x3) with gray level spread on the range [0, 255], (b) Red resulting image by the MVI method, (c) Hue resulting image by the MVI method, (d) reference segmented image.

Another assessment criterion is used to measure quantitatively the segmentation quality. This criterion is based on the determination of the correct and incorrect detection probabilities. In the case where a reference image $R = R_1 \cup R_2$ is available and this image contains two objects (see Fig. 5(d)). The segmentation of the two objects can be considered as a classification. Thus, the result can be measured as the rates of correct classification P_c and false classification P_f :

$$P_c = \frac{N_{1c}}{N_{1r}} \qquad (17)$$

$$P_f = \frac{N_{1f}}{N_{2r}} \qquad (18)$$

where N_{1r} (N_{2r}) is the number of the pixels in the reference R_1 (R_2). N_{1c} is the number of the detected pixels that is relatively correct to R_1, N_{1f} is the number of pixels that belongs to and falsely classified some.

These criteria's have been used by W. Dou [19] to value the efficiency of the segmentation method in the case of abnormal cloths. In the case of our segmentation diagram, they are used to value the method of segmentation in the case of detection of the cells in the medical images or to define the regions of interests in the pictures. We note R_1 the set of the cells in the image, and R_2 the image background, so P_f represents the probability that a pixel of the set of the cells is marked as the background of the picture; P_c represents the probability that a pixel of these cells is marked effectively like part of these cells.

The performance of the between-class variance based thresholding method is quite acceptable. In fact, it can be seen from table II that in Fig. 5(b) that 0.3478% of pixels were incorrectly classified (P_f) by the ME method. Indeed, only 0.1987% of pixels were incorrectly segmented in Fig. 5(c) by using the MVI method. This good performance between these methods can also be easily accessed by visually comparing the segmentation results.

4. CONCLUSIONS

In this paper, we addressed the problem of color image segmentation in different color spaces by using the clustering methods. In this framework, we investigated in particular the choice of the adapted color spaces and the segmentation approach for a specific application.

Misclassified errors and the segmentation sensitivity were used to evaluate the accuracy of the unclassified methods. The maximum P_f and Sen(%) for all cases with or without noise was only 0.1987 and 15.27%, respectively, which is very close to the values obtained by the between-class variance based thresholding (MVI) method. In fact, the MVI method outperforms the entropy based thresholding method by greatly reducing the misclassified pixels in an image.

The MVI clustering method was employed for several color cells images and they could demonstrate significant enhancement in performance compared to other methods, employed for segmenting the same images. The obtained results showed the generic and robust character of the MVI clustering method in the sense where this technique is applied to hue color feature.

Consequently, the color feature hue is proved to be more efficient than RGB color features by this research. The advantages and disadvantages of different color spaces, HSI and RGB, are also given. The MVI clustering method can be useful for color image segmentation.

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