

# Entropy Based Thresholding For Color Image Segmentation

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**Abstract**—In this paper we present a simple and efficient technique of color image segmentation based on new approach for color level selection among a widely set of color space. We still prove the dependence between segmentation results and the used color level. Our method is based on entropy-based thresholding that is able to separate different objects based on the calculated amount of information contributed by each one. The first part of this manuscript is how to proceed to select the best color components which improve the segmentation results.

**Keywords**—entropy; color space; segmentation; color image; thresholding

## I. INTRODUCTION

Color Image segmentation is the process of regrouping or clustering the pixels contained in an image into sets of coherent attributes. Today this process is regarded as one of the fundamental procedures in computer vision application and particularly in image processing, many related application can be mentioned, for example, contrast enhancement [1], feature extraction and association of correspondence. The image analysis may obtained in black-and-white, gray or color space. However, color images contain much more information than that could be delivered by black-and-white images. Segmentation can be performed using a number of methods such as histogram thresholding, feature clustering, use of fuzzy systems and neural networks [2]. There is a number of designs that enable one to determine a proper threshold. For example, the minimization of the variance within a segmented object [3], the maximization of similarity using intelligent computation approaches [4] and the use of soft-computing techniques such as fuzzy logic [5]. In [6], buildings in an urban area are extracted from an aerial image. The result, in cooperation with data from the geographic information system, is applied in town planning and land-use monitoring. Moreover, in [7], moving objects such as road vehicles are detected from aerial surveillance video streams with the use of segmentation. This system has a high application potential in military, law-reinforcement and disaster response operations. The application of image segmentation in agriculture has also been reported. In [8], segmentation of objects, such as fruit,

suffering from occlusion is addressed with a watershed-based approach. Planted crops on the ground can be identified [9] against noise and shadows using a mean-shift based technique.

In this paper we describe the entropy-based thresholding method for color image segmentation. It's a strong technique which can separate the foreground pixels to the background, thanks to the calculated amount of information contributed by each set of pixels. This paper is organized as flows. Selection of the best choice of color component among wide set of color space is explained in section 2. In section 3 we describe the proposed method of segmentation with the determined color space, thus we try to detail how the entropy contribute to separate the features of different objects. Finally results discussion is explained in section 4.

## II. BEST COLOR COMPONENT SELECTION

### A. Used discriminating criterion

The choice of a particular color space is still largely dependent on the application. In this work, we present a range of discriminating criterion commonly used in the literature to select the color components that may be separate the clusters of an image among the set of color space from CIE comity to build hybrid spaces that can improves results in various applications[10]. The selection criterion is intended to measure the discriminating power of a set of attributes. Wapper approach uses directly the recognition rate of the classifier as a selection criterion of attributes spaces. Filter approach simply estimate the discriminating power of a space of attribute based on statistical measurements on a training sample (covariance, correlation). The evaluation of the discrimination power of a feature space is assumed that if the classes are most separated and compact, then the value of the criterion is large or small. For this reason the criterion quoted below are based on the measurement of separating and compactness of classes. These measures require priori knowledge characterize the classes.

### B. Trace ratio criterion

As shown in equation (1) the covariance matrix of inter-class is compared to the total covariance by:

$$J_1(s_l^d) = \text{trace}((T(s_l^d))^{-1} B(s_l^d)) \quad (1)$$

Where B is the dispersion matrix of inter class and T is the global dispersion matrix of inter and intra class. The maximization of  $J_1$  criterion, determine the discriminating power of attribute space, in fact when the value of  $J_1$  is enough higher, then the attribute that constitute the considered space are very discriminate. Value of trace is the sum of diagonal coefficient of square matrix that represents inter and intra class features of different objects in the scheme.

### C. Hotelling criterion

This criterion is similar than the previously one, it is based on the measurement of compactness matrices and degree of class separating. The criterion value is determined by the ratio of the compactness matrix and the matrix of separating power thus the maximization of this criterion gives the degree of discrimination.

$$J_2(s_l^d) = \text{trace}((B(s_l^d))^{-1} W(s_l^d)) \quad (2)$$

Where W is the dispersion matrix of intra class.

### D. Wilks criterion

The discriminate power value is given by:

$$J_3(s_l^d) = \frac{|W(s_l^d)|}{|T(s_l^d)|} \quad (3)$$

Where  $|T(s_l^d)|$  represent the determinant of  $|T(s_l^d)|$  matrix. This criterion will be minimized, if  $J_3$  is enough lower we can say that the attribute space is more discriminating, in practice maximizing the inverse of this criterion will be easier.

### E. Maximum eigenvalue criterion

This criterion is based on the maximum measurement of the largest Eigenvalue of ratio between total dispersion matrix and discriminating power matrix.

$$J_4(s_l^d) = \max_{p=1}^q \Lambda_p((T(s_l^d))^{-1} B(s_l^d)) \quad (4)$$

Where  $\Lambda_p((T(s_l^d))^{-1} B(s_l^d))$  represents the  $p^{th}$  Eigenvalue of  $T(s_l^d)^{-1} B(s_l^d)$  matrix.

### F. Selection of discriminant color component

R. T. Collins and Y. Liu [11] used a method to select the most discriminating color components for tracking objects. Indeed, a measurement of the discriminating power of a color component is used, where we calculate for each color component the ratio of the inter-class and intra-class variance. For a given color component, we measure the separability between object and background by:

- The expected distribution of the pixels of the object and the background relative to the color component; Let  $H_{obj}(i)$  and  $H_{bg}(i)$  are respectively the histogram of pixels that represent object and background.  $p(i)$  and  $q(i)$  are respectively the probability density that measure the membership degree of a pixel to the foreground and background.
- Computing the log-likelihood ratio of these distributions.

$$L(i) = \log \left( \frac{\max\{p(i), \mu\}}{\max\{q(i), \mu\}} \right) \quad (5)$$

We set  $\mu$  to 0.001.  $\mu$  is a small value that prevents dividing by zero or taking the log of zero.

- Calculate the variance ratio of membership likelihood to the foreground and background allowing us to appreciate their separability. For a given degree of membership  $a(i)$ , the variance of  $L(i)$  is given by:

$$\text{var}(L; a) = \sum_i a(i) L(i)^2 - \left( \sum_i a(i) L(i) \right)^2 \quad (6)$$

This is the total variance of the pixels of foreground and background divided by the sum of variances intra class, so the ratio of log-likelihood variance is defined by:

$$VR(L; p; q) = \frac{\text{var}(L; \frac{p+q}{2})}{\text{var}(L; p) + \text{var}(L; q)} \quad (7)$$

The denominator requires the intra-class variance should have a low value for both the object and background, while the numerator reward if the values associated with the object and background are widely separated for this reason the global variance must be high. The most discriminating components are those that increase the variance ratio.

### G. Experimental results

In our experimental results, we have calculated the discrimination criterion and then we have selected the relevant color component for three different samples, we justify that this approach is not generic in fact each sample has its own component because the separability between objects it isn't constant, the three tables below illustrate founded results.

Fig. 1. First Sample



TABLE I. EVALUATION OF DISCRIMINATING COLOR COMPONENT FOR THE FIRST SAMPLE

	$1^{st}$	$2^{nd}$	$3^{rd}$
RGB	1.1033	0.5966	0.6672
XYZ	0.5826	0.5842	0.5914
Luv	0.6513	0.6724	0.8097
Lab	0.6427	0.9421	0.7759
HSL	5.6364	0.5038	0.6361
YUV	0.6180	0.8880	1.0223
YIQ	0.6180	1.0581	1.3188
YCbCr	0.5590	2.3019	1.7618

Fig. 2. Second Sample



TABLE II. EVALUATION OF DISCRIMINATING COLOR COMPONENT FOR THE SECOND SAMPLE

	$1^{st}$	$2^{nd}$	$3^{rd}$
RGB	0.7180	0.6564	0.6593
XYZ	0.5606	0.5650	0.5615
Luv	0.7018	0.8044	0.7665
Lab	0.7068	0.8959	0.7802
HSL	2.6761	0.5023	0.5937
YUV	0.6032	0.5386	0.6361
YIQ	0.6032	0.6505	0.5961
YCbCr	0.6115	1.9836	1.5989

Fig. 3. Third Sample



TABLE III. EVALUATION OF DISCRIMINATING COLOR COMPONENT FOR THE THIRD SAMPLE

	$1^{st}$	$2^{nd}$	$3^{rd}$
RGB	2.0945	0.9144	1.0067
XYZ	0.5455	0.5412	0.5678
Luv	0.6407	0.7289	0.7486
Lab	0.6373	0.7763	0.8110
HSL	1.0128	0.5038	0.8203
YUV	0.7945	0.6885	0.7783
YIQ	0.7945	0.8658	1.0821
YCbCr	0.5650	1.5658	1.5410

Among the various criterion of discriminating power measurement, we have to choose the relevant color component allows to improve segmentation results.

### III. ENTROPY BASED THRESHOLDING FOR IMAGE SEGMENTATION

#### A. Introduction

Many studies have been done in a Few years ago in the literature, we can enumerate Multilevel thresholding selection based on the artificial bee colony algorithm [13], the k-means algorithm, it is a generic classification tool, it may be considered among popular technique, allowing to regroup a set of pixels that having similar features, and become it an homogenous region according its luminance and chrominance nuance. K-means algorithm allows contributing many solutions to overcome bad situations. The k-means algorithm returns a partition of data in which objects (set of pixels) are so near together and so far from objects belonging other cluster. According the manipulated data, many distances can be used such as Euclidian, Mahalanobis or Manhattan distances.

#### B. Entropy based threshold segmentation

The amount of information contained in the segmented objects is adopted as a measure to determine the segmentation rule. The segmentation algorithm is tested on aerial images, on planted fields and building areas.

- Evaluated maximum information: The information measured by entropy can be used to select the color space so that it is the largest among the other color level under the test. The information in a color image are inherited from the scene and coded as color components. Indeed each component can convey different amounts of information, the measured content of the information transmitted by a color component is obtained from the entropy calculated from the probability distribution. Calculating content of information is independent to the color space. For each color component, object will be represented by his normalized histogram then we associated an entropy value for each one, as shown by the following equation.

$$H_r = - \sum \bar{g}_r \log 2(\bar{g}_r) \quad (8)$$

Where  $\bar{g}_r = \frac{g_r}{\sum g_r}$ ,  $G_r = \{g_r\}$  represents histogram of color component  $r$ , and  $\bar{g}_r$  is the normalized histogram, where it may be the probability distribution of a given component. The color component that arises of maximum entropy among considered set of level, it can be selected as the relevant component for image segmentation.

$$c^* = \arg \max_c \{H_c\} \quad (9)$$

- The proposed segmentation algorithm is based on the thresholding selected histogram by maximization of entropy, in fact K. S. Tan et al. [14] are proposed a hybrid approach for color image segmentation using histogram thresholding and Fuzzy C-means method. It is a technique that has been widely adopted by thresholding. There are a lot of models for determining an appropriate threshold, Z. Hou et al. [12] are minimized the variance for image segmentation and object detection. In this method, the distribution of pixels depend on the computed entropy value of each color component, indeed the background and foreground pixels have its own characteristics which allows to discern it from the entropies, thus select relevant threshold.

Let  $\tau$  a candidate threshold,  $k_f = \{1, \dots, \tau\}$  and  $k_b = \{\tau+1, \dots, k\}$  are the indices for background and foreground pixels for a given image such as the pixel values evaluated in selected color component must be in the interval that corresponds to segmented distribution. The threshold  $\tau$  is adjusted according this distribution such a way that  $0 < \tau < k$ .

Entropies of foreground and background are represented by the following equations:

$$H_{f\tau} = - \sum_{f \in k_f} \overline{gc^* f} \log 2(\overline{gc^* f}) \quad (10)$$

$$H_{b\tau} = - \sum_{b \in k_b} \overline{gc^* b} \log 2(\overline{gc^* b}) \quad (11)$$

The explicit form of segmentation threshold is represented by:

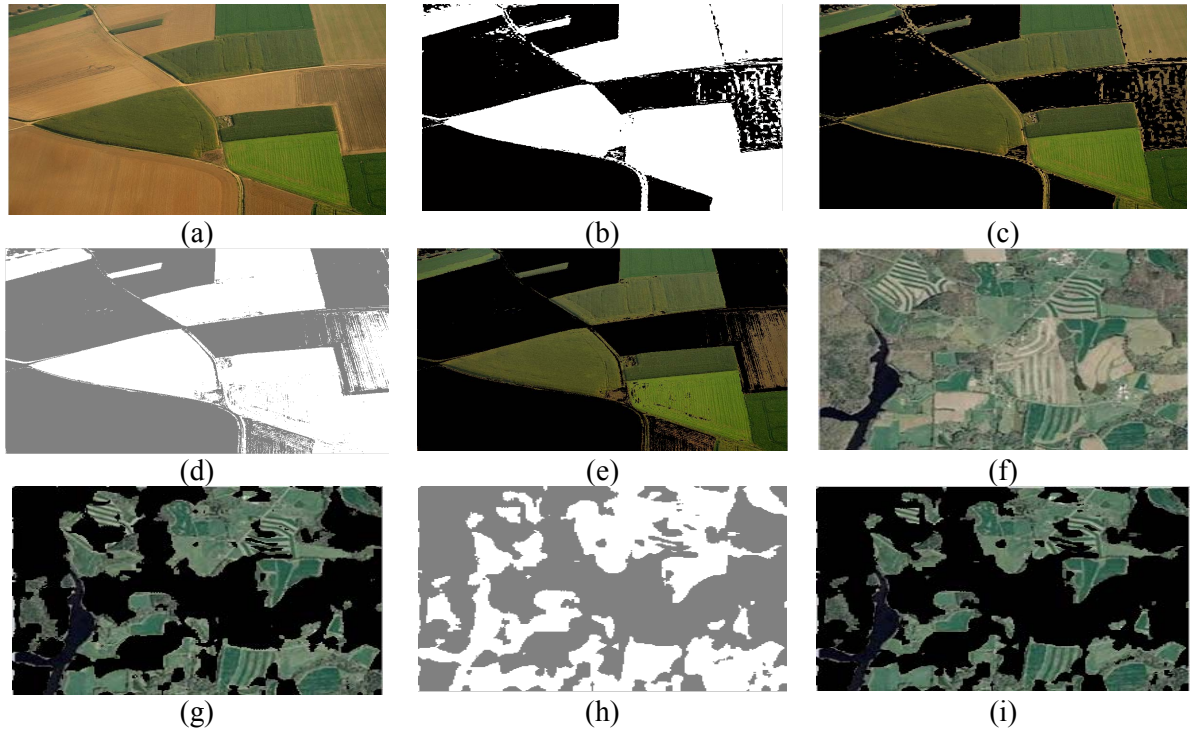
$$\tau^* = \arg \max_{\tau} \{ (H_{f\tau} + H_{b\tau}) - |H_{f\tau} - H_{b\tau}| \} \quad (12)$$

Thus, segmented objects have a maximum of global information illustrated by this term:  $H_{f\tau} + H_{b\tau}$  and minimum of difference information contributed by  $-|H_{f\tau} - H_{b\tau}|$ .

#### IV. EXPERIMENTAL RESULTS

The evaluation of variance criterion for all candidates color component proves the efficiency of this method.

Fig. 4. (a) and (f): Original images. (b),(c),and (g) : Respectively are binary and color results of entropy-based thresholding segmentation. (d), (e),(h) and (i): Respectively are binary and color results of k-means segmentation.





By calculating the variance criterion for all candidates color component, we notice that the color component that gives the best criterion variance ie maximizing this criterion is the one that gives a better result of segmentation among the other color components, this criterion is chosen then as a criterion for discrimination of color components, it is an optimization criterion of colors components that separate the best two different objects.

We discuss the segmentation results with k-means and entropy-based threshold algorithm in the selected color component determined by method explained in sub-section F, through these results we justify the choice of used technique.

The entropic thresholding segmentation in the discriminant color component is compared with the segmentation k means clustering in the same color component. Although the results are very close, we note that the entropy thresholding segmentation has to distinguish the two objects in an image better than k means clustering. This appears, for example, in the image (c) where the entropic thresholding segmentation classifies more green pixels in green areas.

## V. CONCLUSION

The yielded results by entropy-based threshold technique aren't acceptable because pixels are misrepresenting in this level, however the seeking of discriminator color level has contributed to improve the segmentation results. in second way, to bring out our study we have segmented the images by K-means algorithm and comparing the two results we have notice that entropy-based threshold technique is very strong than k-means method

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