

COLOR IMAGE SEGMENTATION USING COLOR SPACE ANALYSIS AND FUZZY CLUSTERING

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ABSTRACT: *This paper presents a new method using color space analysis to obtain a proper number of colors and a good initial estimate of center positions. Then fuzzy c-means algorithm is used to optimally cluster the color space data points projected from an input image. Hence optimal color segmentation can be achieved.*

KEYWORDS: 3-D color space analysis, 3-D pyramiding, 3-D low pass filtering, 3-D object labeling, validity measure of fuzzy c-means algorithm.

1. INTRODUCTION:

A color image comprises of 3 primary colors, red, green and blue. Projecting the color image pixels into the color space constructed by 3 orthogonal axes of R, G, B, one gets a projected color space distribution of the input color image. In the color space, the dots are usually distributed around a number of centers, which are roughly corresponding to the number of colors that the input image contains. The distribution in the color space can be concentrated, can also be widely spread. If it is widely spread, the correct number of centers and their positions for clustering are difficult to estimate.

Color image segmentation methods can be roughly categorized, in this context, as (a) histogram thresholding, for example Ohta et al (1980) [1] -- an Ohlander-type segmentation by dynamic Karhunen Loeve transformation, and Shafarenko et al (1998) [2] -- using watershed transformation; (b) color space clustering, for example Lim & Lee (1990) [3] and Xie & Beni (1991) [4] -- using fuzzy c-means clustering; (c) edge detection and region extraction, for example Healey (1992) [5] -- edge detection guides the color segmentation; (d) Markov random field (MRF) and Gibbs random field (GRF), for example Huang et al (1992) [6] and Liu & Yang (1994) [7] -- using scale space filter (SSF) for coarse segmentation and MRF for refinement, and Chang et al (1994) [8] -- using GRF with k-means clustering; (e) neural network and learning theory, for example Wu et al (1994) [9], Uchiyama & Arbib (1994) [10] and Littman & Ritter (1997) [11]; (f) the various combination of the above techniques. Often color segmentation comprises two stages: coarse segmentation and refinement. It is interesting to look at in detail how these algorithms find the number of colors C . Ohta et al (1980) [1] and Shafarenko et al

(1998) [2] decide C from major peaks (modes) in histogram. Healey (1992) [5] extracts the spatial region to determine the number of colors. Lim & Lee (1990) [3], Huang et al (1992) [6] and Liu & Yang (1994) [7] decide C by using SSF in coarse segmentation. Xie & Beni (1991) [4] uses compactness and separation validity measure. Chang et al (1994) [8] divides the color space into 8 cubes then eliminate unpopulated cubes resulting a $C < 8$. Wu et al (1994) [9] and Littman & Ritter (1997) [10] use only two clusters. Uchiyama & Arbib (1994) [9] pre-selects C to be 8.

Basically the color segmentation differs from color quantization in that it is capable of finding the number of color unsupervised- or dynamically. However, this very question has not been solved satisfactorily. The existing color space clustering algorithms usually make use of various validity measures such as entropy, partition coefficient [12] etc. and repeat the fuzzy c-means algorithm for different number of colors to find the optimal C . These validity measures may not always work. The best validity measure probably is the Xie & Beni's compactness and separability [4], but it is still time consuming.

This paper describes a non-fuzzy classic style method to find a proper number of colors, then fuzzy clustering algorithm is used to refine the result of the non-fuzzy analysis. Fuzzy c-means algorithm can produce good results if the correct number of clusters is known a priori. The method includes color space pyramiding described in Section 2, low-pass filtering in Section 3 and 3-D object labeling (together with center calculation) in Section 4. Section 5 describes briefly the fuzzy c-means algorithm. Section 6 presents the examples of the experiment results. Section 7 concludes the paper.

2. PYRAMIDING:

The color space is usually of the size of $256 \times 256 \times 256$. The dots are usually disjointed one from the other. The number of total dots projected from input image to the color space are equal to the size of the input image, i.e. $N_r \times N_c$, where N_r is the row number and N_c is the column number of the input image. These total number of dots can be considered as total weight of color space objects. In order to make analysis easier a pyramid algorithm [13] is used to reduce the size of the 3-D color space. The pyramid algorithm adds, through out the entire color space, the values of every 8 voxels in a $2 \times 2 \times 2$ cubic into 1 voxel, thus reduces the size of the color space by 8 into the size of $128 \times 128 \times 128$. The reduction is iterated 3 times, effectively reduces the color space to the size of $32 \times 32 \times 32$. The total weight of the objects in the color space, however, is not changed, still equal to $N_r \times N_c$, because the pyramiding does not throw away any weight contained in the original color space.

3. LOW-PASS FILTERING:

The number of objects in the $32 \times 32 \times 32$ color space is still very large. In order to make the dots joint into blocks, a low-pass filter is applied to blur the distribution into connected components/smooth bigger blocks. The low-pass filter averages a voxel's neighborhood volume of $5 \times 5 \times 5$ into a new 3-D buffer, then, after every voxel is averaged, assigns the new 3-D buffer back to the $32 \times 32 \times 32$ color space. Because of this averaging, narrow gaps between heavy objects in the color space become no longer empty, rather they are filled with certain average values or covering clouds. Thus more isolated objects become jointed. This low-pass filter is applied twice and the number of objects is dramatically reduced from hundreds to less than 7, the range that the fuzzy c-means algorithm can be best applied. Experiment shows that intrinsically different colors remain separated, only the similar colors are merged.

4. 3-D OBJECT LABELING:

The objects in the 3-D color space of the size of $32 \times 32 \times 32$ are labeled using 3-D labeling. The 3-D labeling is comprised of a stack of thirty-two 2-D labeling. 2-D binary object labeling is described in most image processing text books such as Gonzalez and Woods [14]. The thirty-two 2-D labeled images are stacked together and the connectedness between objects in neighboring 2-D images are searched and recorded. Similar to 2-D 4-connectedness, a 1st order (nearest neighbourhood) connectedness is used. The information of the connectedness between labeled objects in neighboring 2-D images is used to equalize the labels of objects separated in 2-D but connected in 3-D.

The equalization is done through a square sorting matrix. The square sorting matrix has row number (hence the column number) equal to the total number of labels used in the thirty-two 2-D labeling. The matrix elements are initialized to zero. Each connectedness between objects will set a matrix element to 1. Then a column by column scan is carried out. At one particular column, if any two non-zero elements are encountered (that means the two rows are connected, i.e., not independent), the two rows are merged into one row, the other row is reset to zero. Eventually every row is independent from other rows. Each independent row is assigned a representative label which is consistent and consecutive through out all independent rows. For example, if there are total seven objects labeled by number "1" to "7" and, "1" is connected to "4" and "5", "2" is connected to "5" and "6", "3" and "7" are isolated individual objects, then the matrix will be set as in (1) below where the arrow indicates the merge and reset operation. At the end there are total three independent rows representing three separated connected components. They are each assigned with representative label a, b and c.

Using the consecutive representative labels, all objects in the $32 \times 32 \times 32$ space can be alphabetically labeled and identified. Geometric centers (and other geometrical

properties) for the labeled 3-D objects can then be calculated. The centers thus calculated can be used as good estimate of initial centers for the fuzzy c-means algorithm. The number of colors thus acquired is more clearly meaningful and relevant than those acquired using other validity measures.

$$\begin{array}{c}
 1 \ 2 \ 3 \ 4 \ 5 \ 6 \ 7 \\
 \begin{array}{c}
 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7
 \end{array}
 \begin{bmatrix}
 1 & 0 & 0 & 1 & 1 & 0 & 0 \\
 0 & 1 & 0 & 0 & 1 & 1 & 0 \\
 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 1
 \end{bmatrix}
 \Rightarrow
 \begin{array}{c}
 \begin{bmatrix}
 1 & 1 & 0 & 1 & 1 & 1 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 0 & 0 & 0 & 0 & 0 & 0 & 1
 \end{bmatrix}
 \end{array}
 \begin{array}{c}
 a \\ b \\ c
 \end{array}
 \end{array} \quad (1)$$

5. FUZZY C-MEANS CLUSTERING:

Once the number of colors is known, a standard fuzzy c-means algorithm [12], [15], [16] can be used to cluster the color space objects. The fuzzy c-means algorithm is based on minimization of the following criterion function which is the sum of the squared Euclidean distances between an input sample and a cluster center, weighted by the fuzzy membership functions.

$$J(U, V) = \sum_{i=1}^c \sum_{k=1}^n u_{ik}^m |\bar{x}_k - \bar{v}_i|^2 \quad (2)$$

where $\bar{x}_1, \dots, \bar{x}_n$ are n vectors of input data samples; $V = \{\bar{v}_1, \dots, \bar{v}_c\}$ are cluster centers; \bar{x}_k, \bar{v}_i each has three orthogonal components $\bar{x}_k = (x_R, x_G, x_B)_k$ and $\bar{v}_i = (v_R, v_G, v_B)_i$. $U = \{u_{ik}\}$ is a $c \times n$ matrix, where u_{ik} is the i th membership function on the k th input sample \bar{x}_k , and the membership functions satisfy the following conditions

$$0 \leq u_{ik} \leq 1, \quad i = 1, 2, \dots, c; \quad k = 1, 2, \dots, n \quad (3)$$

$$\sum_{i=1}^c u_{ik} = 1, \quad k = 1, 2, \dots, n \quad (4)$$

$$0 < \sum_{k=1}^n u_{ik} < n, \quad i = 1, 2, \dots, c \quad (5)$$

and $m \in [1, \infty)$ is an exponent weight factor which reduces the influence of small-valued membership functions.

The algorithm iteratively updates the following equations:

$$\bar{v}_i = \frac{\sum_{k=1}^n u_{ik}^m \bar{x}_k}{\sum_{k=1}^n u_{ik}^m}, \quad i = 1, 2, \dots, c \quad (6)$$

$$u_{ik} = \frac{\left[\frac{1}{|\bar{x}_k - \bar{v}_i|^2} \right]^{1/(m-1)}}{\left[\sum_{j=1}^c \left[\frac{1}{|\bar{x}_k - \bar{v}_j|^2} \right]^{1/(m-1)} \right]}, \quad i = 1, 2, \dots, c; \quad k = 1, 2, \dots, n \quad (7)$$

until the change of J in Equation (2) reaches a pre-specified small number, the center locations then become optimal.

Once the centers are refined using the fuzzy c-means algorithm, every color space voxel is assigned to its nearest center. Using the clusters, input color image can be segmented into sub-images thus color segmentation achieved.

6. THE EXPERIMENT RESULTS:

A comparison between the proposed method and that of Xie & Beni's [4] is carried out over fifteen various color images. In Xie & Beni's method [4], the fuzzy c-means algorithm runs repeatedly at various C , the number of colors, starting from 2 to a cutoff number (which is chosen to be 12 in the comparison), to determine an optimal C with respect to the lowest measure of compactness and separability validity.

On average, the labeling method spends 5.67 seconds to find C , whereas Xie & Beni's method takes 684.53 seconds to find C . That is 120 times longer one method over the other. The labeling method often finds a C less by one than that found by the Xie & Beni's method. The smaller C produces clearer results on the

testing images. All these show the advantage of the proposed method over the Xie & Beni's method.

Once a number of colors is obtained the fuzzy c-means algorithm needs only a run for that particular number of colors.

Three experiment examples are shown in the Figure 1 through Figure 16. Figure 1 is the input image for the 1st example, Figure 6 the input image for the 2nd example and Figure 11 the input image for the 3rd example. Rest of the Figures are the segmentation results presented on gray background. For the fuzzy c-means clustering, the exponent weight m is chosen to be 1.5, and the error criterion $\sum_{i=1}^c \sum_{k=1}^n |u_{ik}^{(\alpha)} - u_{ik}^{(\alpha-1)}| \leq \varepsilon = 1$ is used instead of $\Delta J \leq \varepsilon$. The results show that important text information is clearly lifted from the original input images. The machine used is sunOS 5.6.

The time components in using the proposed method are shown in Tabel 1:

TABEL 1

	Color number	Fuzzy color
Images	calculation	segmentation
the 1st example	5.55	3.02
the 2nd example	5.73	3.41
the 3rd example	5.78	44.17

The remaining problem is the noise issue, specially with images containing a large number of colors. Figure 14 is apparently a noisy segmentation. The noise problem might be solved by more sophisticated processing combining color space analysis with image spatial analysis.

7. CONCLUSION:

The paper has presented a new method of color space analysis to derive the number of colors and the initial estimate of center positions. The method is comprised of three sub-processes: pyramiding which reduces the color space to $32 \times 32 \times 32$, low-pass filtering which reduces the number of color space objects to less than 7, and 3-D labeling which identifies each 3-D object and calculates it's geometric center. Once the proper number of colors and good initial center values are obtained, the fuzzy c-means algorithm can achieve the result for which it becomes so well known.

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Figure 1: 1st example.



Figure 2: Segment #1.



Figure 3: Segment #2.



Figure 4: Segment #3.

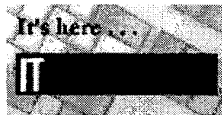


Figure 5: Segment #4.



Figure 6: 2nd example.



Figure 7: Segment #1.



Figure 8: Segment #2.



Figure 9: Segment #3.



Figure 10: Segment #4.

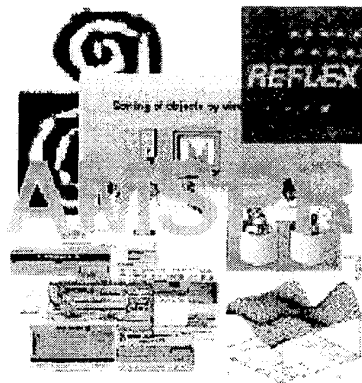


Figure 11: 3rd example.



Figure 12: Segment #1.

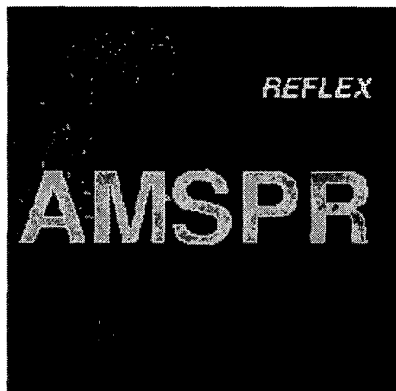


Figure 13: Segment #2.

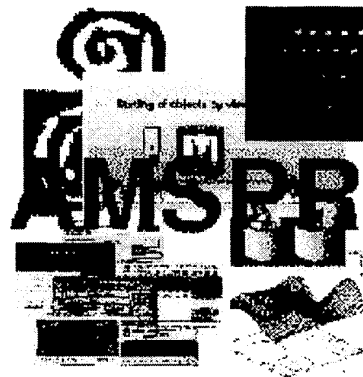


Figure 14: Segment #3.



Figure 15: Segment #4.

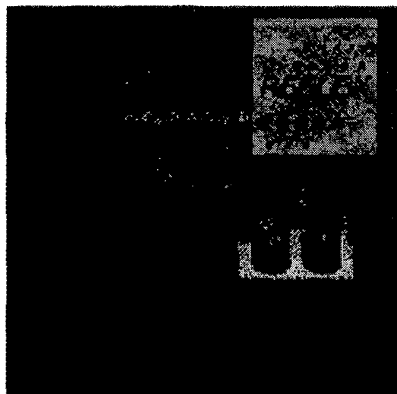


Figure 16: Segment #5.