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Color Image Quantization Using Color Variation Measure

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Abstract-In this paper, a novel color image quantization algorithm is presented. This new algorithm addresses the question of how to incorporate the principle of human visual perception to color variation sensitivity into color image quantization process. Color variation measure (CVM) is calculated first in CIE Lab color space. CVM is used to evaluate color variation and to coarsely segment the image. Considering both color variation and homogeneity of the image, the number of colors that should be used for each segmented region can be determined. Finally, CF-tree algorithm is applied to classify pixels into their corresponding palette colors. The quantized error of our proposed algorithm is small due to the combination of human visual perception and color variation. Experimental results reveal the superiority of the proposed approach in solving the color image quantization problem.

I. INTRODUCTION

Color has been recognized as an important visual cue for image and scene analysis. Research work in color analysis has focused on color image formation, color quantization, human visual perception, image segmentation, color-based object recognition, and image database retrieval. As a basic technique of color image processing, color quantization plays an important role in many aspects mentioned above. Generally speaking, color image quantization is divided into four phases [1]: (1) sampling the original image for color statistics; (2) choosing a color map based on the color statistics; (3) mapping original colors to their nearest neighbors in the color map; (4) quantizing and representing the original image. These four steps are inherently connected with each other in which Steps 1 and 2 influence the final result to a great extent.

A good color quantization technique must consider several factors such as the least distortion, complexity of algorithm, the characteristics of human visual system (HVS) and so forth. Currently, there is not a satisfactory solution to the problem of how to determine the number of colors to be used in the palette while considering human visual perception and the color variation in different image regions. In many cases, only one palette is used for the whole image. However, a single palette can not discriminate different attributes among different regions in the image because these regions have different color variation which can influence human perception sensitivity.

One of the important HVS properties is that different colors and their spatial pattern variation can influence human's color perception sensitivity [2] [3]. Fig. 1 shows the test images with spatial color pattern variations. It can be observed that when color spatial pattern variation increases (from left to right in Fig. 1), human color visual perception sensitivity decreases. This indicates that more colors should be used to discriminate the color nuances of a more homogeneous region, and vice versa.

Furthermore, color quantization is deemed as the prerequisite of many color image segmentation algorithms [4]. Zouagui [5] proposed a new function model based image segmentation framework. This function model consists of five elementary blocks: measure, criterion, control, modification and stop. Using each segmented region's attributes, the segmented image is iteratively modified by the segmentation results from previous iterations. From these two viewpoints mentioned above, we can see that not only color quantization decides the later segmentation result, but also segmented regions' information iteratively influences the measure block which contains the color quantization. In this paper, we propose a new color image quantization algorithm. According to the principles presented in References [2] and [3], the proposed algorithm considers the relationship between the segmented regions and their palette sizes so that the regions which need more colors will be quantized into more color levels.

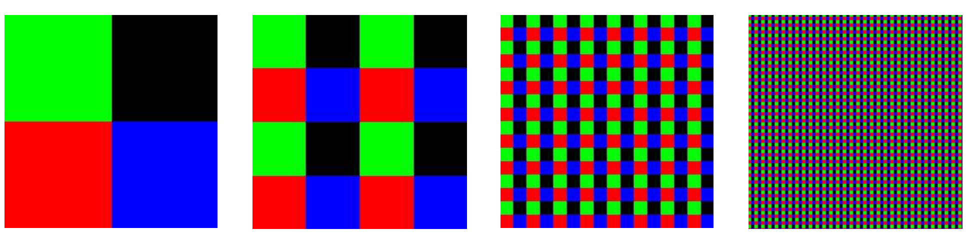


Fig.1. Test patterns of color visual perception sensitivity to spatial color pattern variation.

II. BACKGROUND AND RELATED WORK

Palette design is to select a small number of representative colors from an image that has high color resolution to form a color set. Using this color set or palette, the high-resolution color image can be represented by replacing the original colors with a smaller set of color elements in the palette. In the past, many color quantization algorithms have been proposed such as median-cut algorithm [1], uniform algorithm [1], octree algorithm [6], center-cut algorithm [7] and clustering-based algorithms such as K-means, adaptive clustering algorithm [8].

The basic idea of median-cut algorithm is to divide the colors of the original image into K boxes in the color space. Each box contains the same number of pixels of the original image. The average color value of each box is used as one of the K colors of the color palette. Colors with high pixel numbers can be included into one box; on the other hand, colors with low pixel numbers can not be represented well.

The uniform quantization algorithm divides the color space into subspaces directly, and chooses a group of colors with evenly distributed red, blue and green components. In this algorithm, the palette colors have no relationship with the colors of the original image. Although this algorithm is simple and fast, since not every image contains all the evenly distributed colors, the final result often differs largely from the original image.

The octree algorithm is based on the agglomerative idea which divides a predetermined subdivision of the RGB color space into levels of octants. Like the median-cut algorithm, this method loses color details. The center-cut algorithm repeatedly splits the color set whose bounding box has longest side until K sets are generated. The centers of K sets are used as palette colors. Clustering-based algorithms usually use the minimal distance as the metric for the clustering. The algorithm in [8] uses a 3D-histogram which is fed into an adaptive algorithm to build the palette. A destined pixel-mapping algorithm is applied to classify pixels into their corresponding palette colors.

A few new or modified algorithms have been proposed in recent years. Zhao [9] proposed an improvement of K-means algorithm. Atsalakis divided an image into small windows and quantized the major colors of these windows [10]. In [11], an algorithm integrated with Gamma correction was proposed and proved to be efficient to improve the visual effect of quantized images.

III. ALGORITHM IMPLEMENTATION

A. Color Image Quantization Framework

We propose a new color image quantization framework based on color variation measure. Fig.2 shows the flow chart of the algorithm. CVM image block is the core of the whole algorithm. CVM not only is the prerequisite of the segmentation, but also can guide the quantization of different regions and can depict the inner color variation of the image. Details of this algorithm are discussed in the following sections.

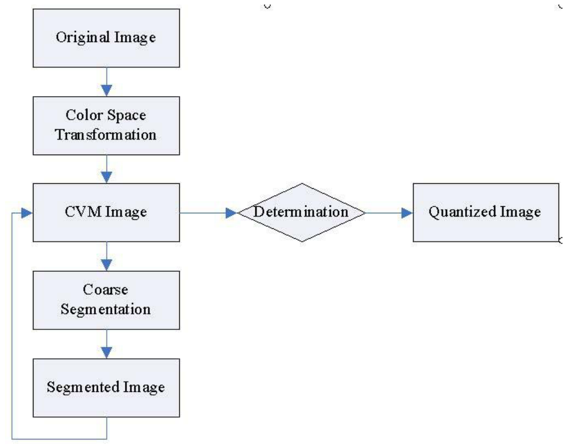


Fig.2. Color image quantization algorithm.

B. Color Space Transformation

Color is perceived by human as combinations of tristimuli R (Red), G (Green) and B (Blue) or three primary colors. It is important to choose a good color space for color image quantization, since the distance measure in color space must conform to human visual perception. CIE color space was developed to represent perceptual uniformity. Furthermore, in CIE color space, color difference can be calculated as the Euclidean distance between two color points.

CIE color space has three primaries, X, Y and Z. Colors can be represented by combinations of X, Y and Z. The X, Y and Z values can be computed from RGB tristimulus coordinates using a linear transformation as shown in (1) and (2).

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} 0.607 & 0.174 & 0.200 \\ 0.299 & 0.587 & 0.114 \\ 0.000 & 0.066 & 1.116 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \tag{1}$$

, and

$$\begin{cases} L = 116\left(\sqrt[3]{\dfrac{Y}{Y_0}}\right) - 16 \\ a = 500\left[\sqrt[3]{\dfrac{X}{X_0}} - \sqrt[3]{\dfrac{Y}{Y_0}} - \right] \\ b = 200\left[\sqrt[3]{\dfrac{Y}{Y_0}} - \sqrt[3]{\dfrac{Z}{Z_0}} - \right] \end{cases} \tag{2}$$

The three parameters, L, a, and b in CIE color space represent the brightness of the color, its position between magenta and green, and its position between yellow and blue, respectively.

C. Color Variation Measure Image

CVM is computed in both horizontal and vertical directions. CVM for each pixel is composed of two positive and two negative components in each direction. For the window size of $(2s+1)\times(2s+1)$, the operation is described below.

Image is first transformed into CIE Lab color space according to (1) and (2). For an $M \times N$ image, the magnitude is normalized as:

$$\Delta\bar{H} = \begin{bmatrix} \bar{H}_1^- & & \bar{H}_1^+ \\ & \bar{0} & \\ \bar{H}_2^- & & \bar{H}_2^+ \end{bmatrix}, \quad \Delta\bar{V} = \begin{bmatrix} \bar{V}_1^- & & \bar{V}_2^- \\ & \bar{0} & \\ \bar{V}_1^+ & & \bar{V}_2^+ \end{bmatrix} \tag{3}$$

These positive and negative components are defined as:

$$\begin{aligned}
\bar{H}_1^- &= \frac{1}{s(s+1)} \sum_{y=y_0-s}^{y=y_0+1} \sum_{x=x_0-s}^{x=x_0+1} \bar{c}(x,y) \\
\bar{H}_1^+ &= \frac{1}{s(s+1)} \sum_{y=y_0-s}^{y=y_0+1} \sum_{x=x_0-1}^{x=x_0+s} \bar{c}(x,y) \\
\bar{H}_2^- &= \frac{1}{s(s+1)} \sum_{y=y_0-1}^{y=y_0+s} \sum_{x=x_0-s}^{x=x_0+1} \bar{c}(x,y) \\
\bar{H}_2^+ &= \frac{1}{s(s+1)} \sum_{y=y_0-1}^{y=y_0+s} \sum_{x=x_0-1}^{x=x_0+s} \bar{c}(x,y)
\end{aligned} \tag{4}$$

$\bar{V}_1^-, \bar{V}_1^+, \bar{V}_2^-$, and $\bar{V}_2^+$ can be calculated in the similar manner as $\bar{H}_1^-$, $\bar{H}_2^-$, $\bar{H}_1^+$, and $\bar{H}_2^+$, respectively. $\bar{c}(x,y)$ denotes the color value (L,a,b) at pixel (x,y).

In order to get the color variation in the horizontal and vertical directions, we calculate the following vectors:

$$\begin{aligned}
\Delta\bar{H}_1(x_0,y_0) &= \bar{H}_1^+(x_0,y_0) - \bar{H}_1^-(x_0,y_0) \\
\Delta\bar{H}_2(x_0,y_0) &= \bar{H}_2^+(x_0,y_0) - \bar{H}_2^-(x_0,y_0) \\
\Delta\bar{V}_1(x_0,y_0) &= \bar{V}_1^+(x_0,y_0) - \bar{V}_1^-(x_0,y_0) \\
\Delta\bar{V}_2(x_0,y_0) &= \bar{V}_2^+(x_0,y_0) - \bar{V}_2^-(x_0,y_0)
\end{aligned} \tag{5}$$

The scalars $\|\Delta\bar{H}_1(x_0,y_0)\|$, $\|\Delta\bar{H}_2(x_0,y_0)\|$, $\|\Delta\bar{V}_1(x_0,y_0)\|$, $\|\Delta\bar{V}_2(x_0,y_0)\|$ give the color variation in the horizontal and vertical directions. The ultimate value of color variation at pixel (x_0,y_0) can be calculated as following:

$$M(x_0,y_0) = \sqrt{\begin{array}{l} \|\Delta\bar{H}_1(x_0,y_0)\|^2 + \|\Delta\bar{H}_2(x_0,y_0)\|^2 \\ + \|\Delta\bar{V}_1(x_0,y_0)\|^2 + \|\Delta\bar{V}_2(x_0,y_0)\|^2 \end{array}} \tag{6}$$

We use $M(x_0,y_0)$ as the CVM to depict the image's interior color variation. Fig. 3 shows the CVM of the flower garden image using 256-level grayscale image.

D. Coarse Segmentation

The goal of our algorithm is to use the principle of human perception to color variation to quantize color image. We adopt a region growing and merging based algorithm to coarsely segment the image. For region growing and merging algorithm, it is required to specify seeds as the starting points of the region growing which directly influence final segmentation results. If the chosen seeds can not typify the attributes of different regions, the segmented regions will not be correct and the segmentation process will be prolonged

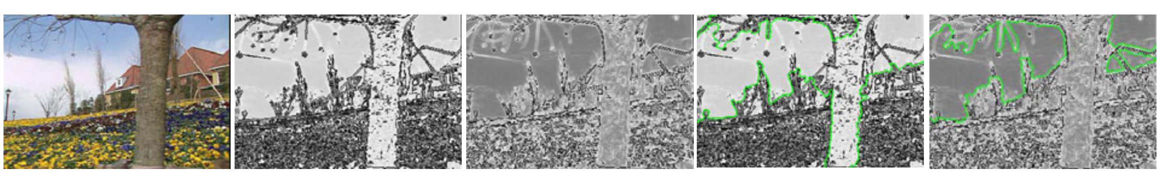
In this paper, using the CVM image, we quantize CVM values of all the pixels to certain levels. According to the estimation of the quantized CVM values, we use the method in [12] to obtain the threshold T. If the CVM value of a pixel is less than T, it is specified to be a seed point, which can be merged with other neighborhood pixels to form candidate seed area. If the number of pixels in candidate seed area exceeds the corresponding numbers in Table I, it will be recognized as the seed area.

TABLE I
MINIMUM PIXEL NUMBERS TO FORM SEED AREA AT DIFFERENT IMAGE SIZES.

Image Size (min(width, height)	Min Seed (pixels)
≤ 128	64
≤ 256	256
≤ 512	1024

After the specification of the seed areas, all pixels are grouped into two categories: seed area pixels and non-seed area pixels. The non-seed area pixels are needed to be merged into their corresponding segmented regions. The strategies are following:

(1) remove the holes in the seed areas by considering their adjacent seed area pixels;
(2) if a non-seed area is adjacent to only one seed area, it will be merged into that seed area; if it is adjacent to more than one seed area, it will be merged into the seed area that has



(a) (b) (c) (d) (e)

Fig. 3 CVM image of "Flower Garden" image. (a) original image, (b) CVM image using 3×3 window, (c) CVM image using 5×5 window, (d) Segmentation of (b), (e) Segmentation of (c).

the shortest distance in CIE Lab color space;

(3) in each iteration, the mean color of every seed area is recomputed until there is no non-seed area.

For the areas whose pixel number is less than 50, they will be merged into the adjacent larger areas. The segmentation results are shown in Figs. 3 (d) and (e).

E. *Color Quantization Based on CVM Image*

After coarse segmentation, each pixel will be assigned a class label to form a class map. In this class map, pixels are grouped into different region labels. Because different segmented regions have different attributes of homogeneous regions, whose color variations are also different. Therefore, calculating the statistics of pixel CVM distribution of different regions can help judge whether the number of quantization levels is valid. If one segmented region has a smooth color variation, it should be given more quantization levels. This is because human visual perception sensitivity increases as the color variation decreases. More color quantization levels result in more accurate color representation to HVS. On the other hand, the region of more complex color variation should be given fewer color levels.

In each segmented region, CVM values of all pixels are used to calculate the region's homogeneity. Assume that the image has m segmented regions and λ_m denote the region homogeneity degree of these regions. λ_m are defined as following:

$$\lambda_m = \sum_{p(i,j)\in R_m} \varepsilon_{p(i,j)} \tag{7}$$

, and

$$\varepsilon_{p(i,j)} = \sum_{\substack{p(x,y)\in R_m \\ x=i\pm1, y=j\pm1}} |M_{p(i,j)} - M_{p(x,y)}| \tag{8}$$

We can see that a smaller λ_m represents a more homogeneous region, which should be assigned more colors. In order to keep the integrity of the perception of the whole image, we need to consider the color variation degree and homogeneity degree simultaneously. Firstly, we use the K-means algorithm on the whole image to get the color number of every segmented regions $N_{K1,} N_{K2,} \cdots, N_{Km}$. Secondly, we use CVM to get the number of colors for each segmented region.

$$N_{Ci} = (\text{int})\left(1 - \frac{\lambda_i}{\sum_{j=1}^{m}\lambda_j}\right) \times N \tag{9}$$

We consider three cases to get final colors of each region to keep a balance:

(1) If $N_{Ki} > N_{Ci}$, larger color variation, the region R_i should be given fewer colors, visual perception sensitivity is modified as:

$$N_i = N_{Ci} + \frac{N_{Ki} - N_{Ci}}{2}, \quad i = 1, 2, \cdots, m \tag{10}$$

(2) If $N_{Ki} < N_{Ci}$, lower color variation, the region R_i should be given more colors, visual perception sensitivity is modified as:

$$N_i = N_{Ki} + \frac{N_{Ci} - N_{Ki}}{2}, \quad i = 1, 2, \cdots, m \tag{11}$$

(3) If $N_{Ki} = N_{Ci}$, color numbers are defined as:

$$N_i = N_{Ki} = N_{Ci} \tag{12}$$

We then use CF-tree method [11] to quantize each segmented region according to its number of colors

IV. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed algorithm, we use four 24-bit 512×512 images for the experiments. These images were: "Flower Garden", "Baboon", "Lena" and "Peppers" as shown in Fig. 4.

We use MSE (Mean Square Error) to compare the difference between the original image and the quantized image. The MSE is defined as follow:

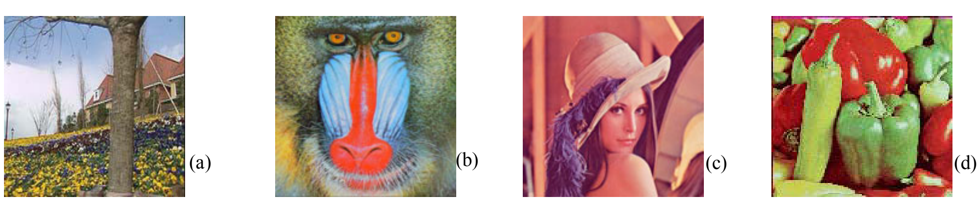


Fig. 4. (a) Flower garden; (b) Baboon; (c) Lena; and (d) Peppers.

(a) (b) (c) (d) (e)

Fig. 5. 256 colors: (a) Proposed method; (b) Center-Cut; (c) K-means; (d) SOM; (e) Octree; and (f) PGF.

(a) (b) (c) (d) (e) (f)

Fig. 6 64 colors: (a) Proposed method; (b) Center-cut; (c) K-means; (d) SOM; (e) Octree; and (f) PGF.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} d\left(c[i,j], q\left(c[i,j]\right)\right)^2 \qquad (13)$$

In (13), $c[i,j]$ and $q\left(c[i,j]\right)$ are original pixels and quantized pixels, respectively. MN is the total number of pixels in the image and $d(x,y)$ is Euclidean distance between color x and color y.

Smaller MSE means better image representation. For the proposed algorithm and all others for comparison, the tested images are quantized into 256, 128, 64, 32 and 16 colors. Table 2 shows the performance measured by MSE. As examples, Figs. 5 and 6 show the "Flower Garden" quantization results of 256 and 64 colors, respectively. Algorithms for comparison include center-cut method [7], K-means method, SOM method [13], octree method [8] and PGF method [14].

As shown in Figs. 5 and 6, the homogeneous blue sky region is quantized with more colors. On the other hand, in the flowers and garden regions with larger color variation, fewer colors are assigned. As shown in Table 2, our proposed algorithm is slightly better than Center-cut and SOM and significantly better than the rest of the methods for comparison.

V. Conclusion

We propose a color image quantization algorithm which considers human visual perception to color variation sensitivity. It first transforms the image from RGB color space into CIE Lab color space and then calculates the horizontal and vertical CVM values. Secondly, region growing and merging algorithm is used to coarsely segment the CVM image to obtain the class label of each pixel and the number of colors in each region. Thirdly, K-means is used to recalculate the each region's number of colors to compare with the number obtained from the second step to maintain a color balance of the whole image. Finally, CF-tree method is adopted to quantize each region using the calculated number of colors.

In solving the color image quantization problem, a single palette can not always perform well for both homogeneous and inhomogeneous regions, because human visual perception to these regions is different. The proposed algorithm is a better choice to solve this problem. Our experiments illustrate that the proposed algorithm is superior to other algorithms. In future work, we will use the proposed color quantization method for other image processing problems such as color image segmentation, content-based image retrieval, image compression and so forth.

VI. References

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TABLE. II
THE COMPARATIVE PERFORMANCE IN TERMS OF THE MSE VALUES ON 24-BIT COLOR IMAGES OF PROPOSED ALGORITHM, CENTER-CUT ALGORITHM, K-MEANS ALGORITHM, SOM ALGORITHM, OCTREE ALGORITHM AND PGF ALGORITHM.

24-bit images	# of Colors	Proposed algorithm (MSE)	Center Cut (MSE)	Median Cut (MSE)	SOM (MSE)	Octree (MSE)	PGF (MSE)
Flower Garden	16	665	690	937	681	1033	902
	32	402	417	481	409	496	437
	64	283	301	312	297	334	305
	128	149	162	161	151	172	158
	256	95	99	109	93	115	104
Baboon	16	668	802	1037	729	1192	943
	32	415	450	682	423	699	586
	64	257	279	335	266	383	291
	128	155	192	197	120	256	202
	256	102	129	143	109	157	133
Lena	16	271	315	427	272	480	381
	32	134	196	239	139	273	198
	64	82	130	142	83	137	129
	128	47	85	79	52	85	81
	256	31	49	42	21	48	43
Peppers	16	469	629	967	481	1069	883
	32	257	380	582	298	626	527
	64	150	267	295	199	320	273
	128	88	153	158	129	149	146
	256	70	102	96	77	101	95