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# On Color Image Quantization by the K-Means Algorithm

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**Abstract.** In this paper we show the main properties of k-means algorithm as a tool for color image quantization. All experiments have been carried out on color images with different number of unique colors and different colorfulness. We have tested the influence of methods of determination of initial cluster centers, of choice of distance metric, of choice of color space. In our tests we have used two dimensions of palette (256,16) and three different measures for quantization errors. The results of k-means technique have been compared with quantized images from commercial programs.

## 1 Introduction

There is not a problem to observe that in each digital color image appears only a small subset of all possible 16,7 millions colors. Color image quantization is the process of transformation of a true color image (eight bit onto each color component) into an image consisting of a small number of specially selected colors (color palette). This process is very often used as an auxiliary operation in computer vision and computer graphics. Color quantization is widely presented in color image processing handbooks [3, 2]. New colors are selected by minimizing the color difference between the original image and the quantized image. Low value of color difference (quantization error) needs a palette designed for the particular image. The quantization error depends on the number of colors in the palette (e.g. 256, 64, 16 colors), the method of choice of colors for the palette and the pixel classifying technique. Color quantization is a kind of lossy compression technique. Many color image quantization techniques based on hierarchical or iterative (partitional) scheme have been proposed in the past. As a generally statement, it may be found that the hierarchical methods are faster than the iterative methods but they have larger quantization errors. Frequently used iterative technique is named k-means algorithm.

The purpose of this paper is to show the main properties of k-means algorithm as a tool for color image quantization. This is done by testing a few color images with different number of unique colors. Three methods of determination of initial cluster centers: randomly from color space, randomly from image, and by uniform partitioning of gray scale are considered. Two metrics in two color spaces (RGB, CIELAB) are tested. We propose to use different measures of quantization errors. First of all, measures that are popular in the color community i.e. MSE and $\Delta E$. Apart from these classical measures we try to use other evaluation function: the colorfulness of image [4]. This approach assumes that the colorfulness of the quantized image should be equal to the colorfulness of the original image. Additionally we called attention on color quantization as presegmentation, which can reduce the complexity of the segmentation problem. We also present the quantization errors as a function of decreasing palette size (256 colors, 16 colors). Quantization results are compared with results from such commercially available programs as PhotoPaint and Photoshop.

## 2 Short description of k-means technique

K-means as clustering technique has been developed in the sixties and already has been described in classical Anderberg's handbook [1]. During the first step of k-means algorithm a fixed number of clusters and initial cluster centers in the color space are chosen. The main idea is to modificate the positions of cluster centers so long as the sum of distances between all points of clusters and their cluster centers will be minimal. During these modifications all points are allocated to closest cluster centers using a predefined metric. The most typical used metrics are: the Euclidean distance and the City Block metric. After each allocation a new positions of cluster centers are computed as arithmetical means of cluster points. The algorithm usually stops if the difference between new and old positions of cluster centers is too small. K-means converges to a locally optimal solution. Received results depend on different factors such as method of determination of initial cluster centers, used color space, applied metric etc. On the other hand there is one of the fastest methods to perform clustering.

## 3 The choice of test images

For investigations a representative set of five color images has been chosen. These images have the same spatial resolution ($640 \times 480$ pixels) and are presented in Fig. 1. The choice was based on calculating the number of unique colors present in the image. Table 1 presents data about chosen images.

**Table 1.** Number of colors in the test images

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| Number of colors | 40523 | 49759 | 66634 | 78805 | 95481 |

In our set of images we have images with small number of unique colors (Chart, Duck), with middle number (Landscape) and with large number of unique colors (Characters, Mountains). From other point of view, we can characterize color images using their perceptual features e.g. colourfulness. Therefore we computed colorfulness of images using metric proposed in [4] (more details about metric see in Section 7). The results of this computations are presented in Table 2.

**Table 2.** Values of colorfulness in the test images

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| Colorfulness | 96,56 | 15,60 | 35,92 | 88,31 | 46,04 |

If we use semantic attributes of colorfulness, then we can correlate the names of images with these attributes: Duck - slightly colorful, Landscape - moderately colorful, Mountains - averagely colorful, Characters - highly colorful and Chart - extremely colorful. Now we are certain that our set of color images is representative: our images "stretch" along the whole scale of colorfulness. By the way, the extremely colorful image Chart has the smallest number of unique colors.

## 4 Methods of determination of initial cluster centers

However classical k-means technique has few "degree of freedom". First of all we should determine the initial cluster centers i.e. starting points of algorithm. We can find these points in whole color space or in set of colors of image pixels or on the gray scale line by its dividing into equal segments. We have tested these three approaches during color quantization to 256 and 16 colors. In each case we evaluated the results using two kinds of values:

$$RSME = \frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{N}\sqrt{(R_{ij}-R^{*}_{ij})^2+(G_{ij}-G^{*}_{ij})^2+(B_{ij}-B^{*}_{ij})^2} \quad (1)$$

$$\Delta E = \frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{N}\sqrt{(L_{ij}-L^{*}_{ij})^2+(a_{ij}-a^{*}_{ij})^2+(b_{ij}-b^{*}_{ij})^2} \quad (2)$$

where: $R_{ij}, G_{ij}, B_{ij}$ are color components in original image, $R^{*}_{ij}, G^{*}_{ij}, B^{*}_{ij}$ are color components in quanitzed image and similarly for CIE Lab components.

Tables 3–6 contain the results of experiment. We can see that in the majority of cases the smaller values of quantization error are achieving for initial cluster centers coming from image. Additionally, we observe that color quantization error is growing if the number of colors in the palette is decreasing. The Fig. 2 shows it for three different palette (256, 64, 16) colors.

**Table 3.** RMSE values for images quantized to 256 colors

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| From space | 3,78 | 5,62 | 5,52 | 6,25 | 7,17 |
| From image | 2,37 | 2,27 | 2,84 | 4,23 | 3,34 |
| From gray-scale | 2,92 | 2,54 | 3,12 | 4,70 | 3,41 |

**Table 4.** $\Delta E$ values for images quantized to 256 colors

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| From space | 1,63 | 2,12 | 1,92 | 9,02 | 3,52 |
| From image | 1,13 | 1,11 | 1,17 | 3,83 | 1,83 |
| From gray-scale | 1,40 | 1,26 | 1,30 | 6,15 | 2,00 |

**Table 5.** RMSE values for images quantized to 16 colors

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| From space | 18,80 | 12,19 | 11,56 | 14,37 | 14,17 |
| From image | 21,61 | 7,22 | 8,68 | 14,71 | 11,33 |
| From gray-scale | 25,38 | 7,24 | 8,91 | 13,76 | 11,13 |

**Table 6.** $\Delta E$ values for images quantized to 16 colors

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| From space | 6,91 | 3,53 | 3,66 | 14,38 | 5,52 |
| From image | 8,21 | 2,52 | 3,15 | 11,49 | 5,03 |
| From gray-scale | 9,48 | 2,47 | 2,79 | 13,49 | 4,69 |

## 5 The choice of metric

Other "degree of freedom" is related with the choice of distance metric in clustering process. We considered two classical metrics for clustering in RGB space: L1 (city block metric) and L2 (Euclidean metric):

$$L1 = |R_1 - R_2| + |G_1 - G_2| + |B_1 - B_2| \tag{3}$$

$$L2 = \sqrt{(R_1 - R_2)^2 + (G_1 - G_2)^2 + (B_1 - B_2)^2} \tag{4}$$

Tables 7–10 show the results for different dimensions of palette (256,16) and different measures of quantization error (RMSE, $\Delta E$). Almost in all cases the quantization error is smaller for L2 metric. In further investigations we used L2 metric and started with clustering process from initial cluster centers that were randomly chosen from all colors of the image.

**Table 7.** RMSE values for images quantized to 256 colors using different metrics

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| L2 | 2,37 | 2,27 | 2,84 | 4,23 | 3,34 |
| L1 | 2,42 | 2,32 | 2,92 | 4,34 | 3,41 |

**Table 8.** $\Delta E$ values for images quantized to 256 colors using different metrics

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| L2 | 1,13 | 1,11 | 1,17 | 3,83 | 1,83 |
| L1 | 1,16 | 1,12 | 1,21 | 3,92 | 1,87 |

**Table 9.** RMSE values for images quantized to 16 colors using different metrics

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| L2 | 21,61 | 7,22 | 8,68 | 14,71 | 11,33 |
| L1 | 22,84 | 7,08 | 8,92 | 14,68 | 11,39 |

**Table 10.** $\Delta E$ values for images quantized to 16 colors using different metrics

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| L2 | 8,21 | 2,52 | 3,15 | 11,49 | 5,03 |
| L1 | 8,82 | 2,53 | 3,31 | 11,72 | 5,07 |

## 6 The choice of color space

The clustering process can be organized in different color spaces. Among color spaces a special role plays the CIE Lab color space. The Euclidean distance in this space is approximately equal to the perceptual difference between colors. Therefore we investigated color quantization using both spaces: RGB and CIELAB. Tables 11–14 show the results for different dimensions of palette (256,16) and different measures of quantization error (RMSE, $\Delta E$). We can observe here some ambivalence: if we use for evaluation RMSE values (based on RGB space) then we achieve that quantization errors for RGB-based k-means clustering are smaller. But if we use for evaluation $\Delta E$ values (based on CIELAB space) then we achieve that quantization errors for CIELAB-based k-means clustering are smaller.

**Table 11.** RMSE values for images quantized to 256 colors using different color spaces

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| RGB | 2,37 | 2,27 | 2,84 | 4,23 | 3,34 |
| CIELAB | 2,90 | 2,85 | 3,61 | 5,54 | 4,19 |

**Table 12.** $\Delta E$ values for images quantized to 256 colors using different color spaces

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| RGB | 1,13 | 1,11 | 1,17 | 3,83 | 1,83 |
| CIELAB | 0,89 | 0,93 | 0,97 | 3,03 | 1,52 |

**Table 13.** RMSE values for images quantized to 16 colors using different color spaces

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| RGB | 21,61 | 7,22 | 8,68 | 14,71 | 11,33 |
| CIELAB | 23,46 | 8,05 | 9,64 | 21,15 | 13,61 |

**Table 14.** $\Delta E$ values for images quantized to 16 colors using different color spaces

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| RGB | 8,21 | 2,52 | 3,15 | 11,49 | 5,03 |
| CIELAB | 6,48 | 2,42 | 2,36 | 10,31 | 4,26 |

## 7 Colorfulness for evaluation of color quantization results

In order to decide above presented dilemma we can use additional evaluation function. This function can be the colorfulness M of image [4]. The quantization error can be expressed as colorfulness difference between original and quantized images. We calculated colorfulness using following formula:

$$M = \sqrt{\sigma_{rg}^2 + \sigma_{yb}^2} + 0.3 \cdot \sqrt{\mu_{rg}^2 + \mu_{yb}^2} \tag{5}$$

where: $\sigma$ and $\mu$ are the standard deviation and the mean value of the pixel cloud along direction described by subscripts, $rg = R - G,\ yb = 0.5(R + G) - B$. Tables 15–18 contain the results of experiment. We can see that in the majority of cases the smaller values of colorfulness difference are achieving for CIELAB color space. Color quantization can be also used as tool for presegmentation. We can see this potential application in Fig. 3 if we use pseudocolorizing for quantized images, particularly for 16 colors.

**Table 15.** Values of colorfulness in the original and quantized images (RGB space)

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| Original | 96,56 | 15,60 | 35,92 | 88,31 | 46,04 |
| RGB 256 | 96,49 | 15,20 | 35,75 | 87,90 | 45,77 |
| RGB16 | 90,60 | 13,61 | 34,09 | 84,21 | 42,94 |

**Table 16.** Values of colorfulness in the original and quantized images (CIELAB space)

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| Original | 96,56 | 15,60 | 35,92 | 88,31 | 46,04 |
| LAB 256 | 96,47 | 15,36 | 35,77 | 87,93 | 45,84 |
| LAB16 | 93,47 | 14,33 | 35,38 | 80,45 | 44,59 |

## 8 Comparison between the k-means quantization and techniques used in commercial programs

Many commercial graphical programs enable users to reduce the number of image colors. We can compare the results from k-means algorithm to the popular programs: Corel

PhotoPaint v.11 and Adobe Photoshop v.7. From few algorithms used in these programs we have chosen following: Optimized (PhotoPaint), Adaptive (PhotoPaint) and Adaptive (Photoshop). Tables 17–20 show the results of comparison for different dimensions of palette (256,16) and different measures of quantization error (RMSE, $\Delta E$). In the case of 256 colors the quantization errors (RMSE, $\Delta E$) of k-means algorithm are smaller than in the case of commercial programs. In the case of 16 colors the superiority of k-means is not so distinctly expressed. The general drawback of k-means technique in comparison with commercial algorithms of color quantization is its longer execution time.

**Table 17.** RMSE values for images quantized to 256 colors using different methods

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| k-means | 2,37 | 2,27 | 2,84 | 4,23 | 3,34 |
| Paint_optim | 2,54 | 2,31 | 2,96 | 3,92 | 3,55 |
| Paint_adapt | 4,65 | 4,14 | 4,40 | 5,38 | 4,29 |
| Photo_adapt | 4,05 | 2,68 | 4,33 | 9,91 | 4,87 |

**Table 18.** $\Delta E$ values for images quantized to 256 colors using different methods

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| k-means | 1,13 | 1,11 | 1,17 | 3,83 | 1,83 |
| Paint_optim | 1,21 | 1,16 | 1,23 | 5,61 | 1,95 |
| Paint_adapt | 2,15 | 2,03 | 1,81 | 9,74 | 2,38 |
| Photo_adapt | 1,98 | 1,30 | 1,76 | 12,81 | 2,52 |

**Table 19.** RMSE values for images quantized to 16 colors using different methods

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| k-means | 21,61 | 7,22 | 8,68 | 14,71 | 11,33 |
| Paint_optim | 22,15 | 7,38 | 8,62 | 13,60 | 13,20 |
| Paint_adapt | 32,15 | 10,97 | 10,53 | 20,53 | 13,25 |
| Photo_adapt | 24,86 | 6,81 | 10,21 | 17,74 | 11,91 |

**Table 20.** $\Delta E$ values for images quantized to 16 colors using different methods

| | Chart | Duck | Landscape | Characters | Mountains |
|---|---|---|---|---|---|
| k-means | 8,21 | 2,52 | 3,15 | 11,49 | 5,03 |
| Paint_optim | 7,00 | 2,63 | 2,62 | 12,58 | 5,01 |
| Paint_adapt | 11,06 | 3,23 | 3,49 | 16,82 | 5,52 |
| Photo_adapt | 7,44 | 2,39 | 3,00 | 16,73 | 4,82 |

## 9 Conclusions

K-means clustering technique used as tool for color quantization produces good quality results. They are not bad from images quantized by commercial programs. Researched method works good with initial cluster centers chosen from image colors, L2 distance metric and clustering in CIELAB color space. Colorfulness can be used for choice of representative set of color images and as additional measure of quality of color quantization.

## References

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a) b) c) d) e)

**Fig. 1.** Color images chosen for tests: a) Chart, b) Duck, c) Landscape, d) Characters, e) Mountains. Image resolution: $640\times480$ pixels.

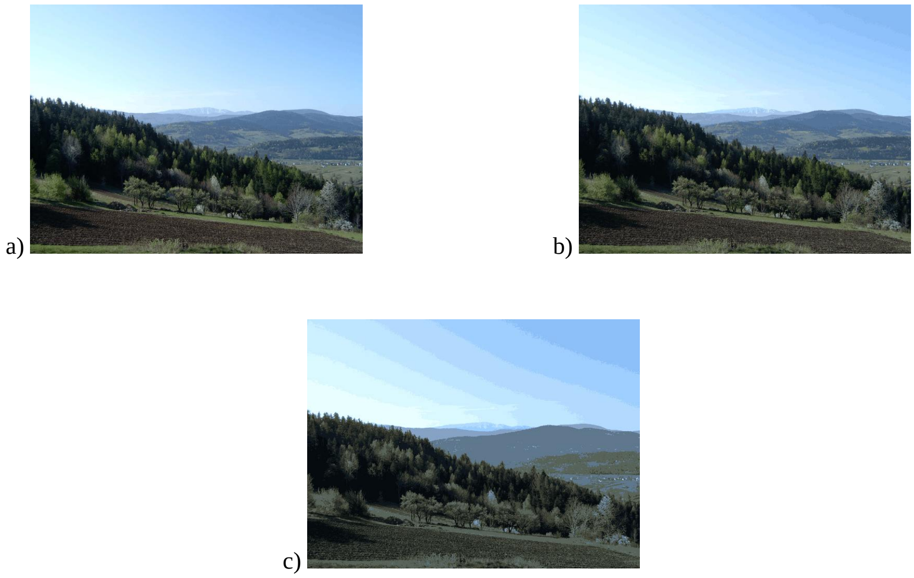


**Fig. 2.** Results of k-means based color image quantization of the image Mountains: a) quantization to 256 colors, b) quantization to 64 colors, c) quantization to 16 colors.

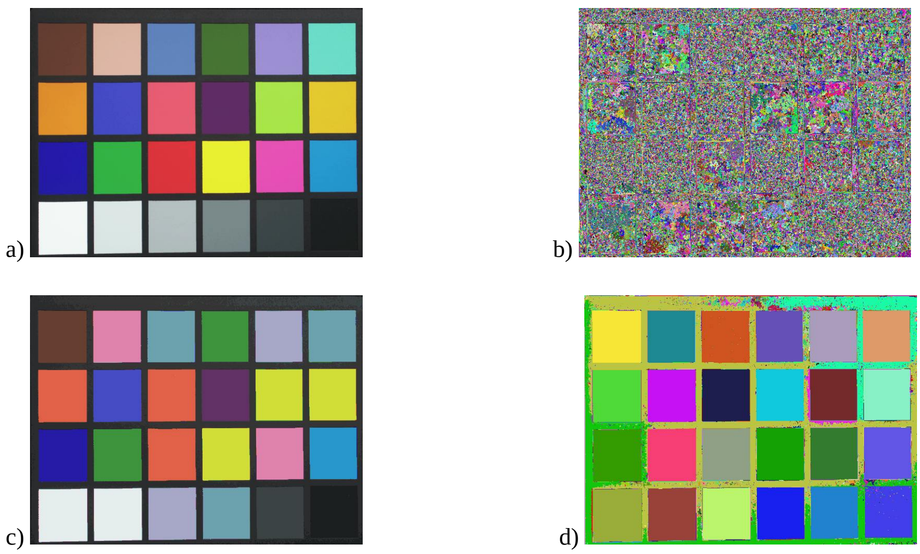


**Fig. 3.** Different versions of the image Chart: a) True color version of the image Chart quantized to 256 colors, b) Pseudocolor version of the image Fig. 3a contains 123633 regions, c) True color version of the image Chart quantized to 16 colors, d) Pseudocolor version of the image Fig. 3c contains 3330 regions.