# Choice of distance metrics for RGB color image analysis

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## Abstract

*Many image clustering algorithms use distance metric in the process of taking decision. When dealing with color images, a distance metric will be used to decide whether two pixels or regions are closed. Colorimetric distances proposed by CIE(Commission Internationale de l'Eclairage) are often used in Lab color space because it is a uniform chromaticity space. However, RGB color space is useful to image processing and instead of converting color image from RGB to another color space before processing, it might be interesting to have the same or better results without changing the color space. In our work, we implement different distance metrics and compare the result of k-mean clustering algorithm in RGB color space to the one in L*a*b* with the colorimetric distance. Two evaluation criteria have been used and we conclude that being in RGB color space and choosing adequately the distance metric, we obtain better segmentation results.*

***Keywords***: *distance metric, color image, color space.*

## Introduction

In many color image segmentations algorithms the metric distance is used to compare two color vectors or two regions. In most of cases, the color space used is the ones considered as perceptually uniform. These color spaces was proposed in 1976 by CIE [1].
So the color image segmentation algorithms often convert color images from RGB space to L*a*b* or L*u*v* color space and then apply the Euclidian distance metric for colors comparison. In our work, we maintain the image in RGB space and then use various distance metrics to determine the one that gives the best results for image segmentation. We present the color spaces and distance metrics. K-mean algorithm will enable us to conclude.

## Color spaces

In color image classification or segmentation, one of the frequently encountered problems is to find the color space so that distance is proportional to one's ability to perceive changes in color.
RGB color space results from the transformation of the spectral power distribution in a three-dimension vector. This color space is device-dependant and gives sometimes negative values. CIE has proposed XYZ color space to overcome these drawbacks. Many other color spaces have been adopted in industries.
MacAdam has demonstrate that CIE chromaticity diagram presents limitations: this representation is non-uniform[2]. He's deduced from the former a uniform representation. Later in 1976 there was a large industry agreement on two standards CIELAB (L*a*b*) and CIELUV (L*u*v*). The uniformity in these color spaces permit to define the colorimetric distance which is proportional to color difference.

## Distance metrics

A distance is a [3] function d with nonnegative real values, defined on the Cartesian product E x E of a set E. It is called a metric on E if for every x,y,z ϵ E:
- d (x,y)=0 if x=y (the identity axiom);
- d (x,y) + d (y,z) ≥ d (x,z) (the triangle inequality);
- d (x,y)= d (y,x) (the symmetry axiom).

### *Minkowsky distance*

Minkowsky distance is a general form of many other distance measures.

$$d(x,y) = \left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{1/p} \quad (1)$$

### *Euclidian distance*

This distance is a Minkowsky distance for p=2. It measures straight-line distance between two points.

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (2)$$

### *Canberra distance*

Introduced in 1966 [4] and modified in 1967, this distance is useful for data scattered around an origin.

$$d(x,y) = \sum_{i=1}^{n} \frac{|x_i - y_i|}{|x_i + y_i|} \quad (3)$$

Each term of the summation has value between zero and one. In the particular case of the numerator and the denominator equal to zero, the term is defined equals to zero.

### *Squared chords distance*

Squared chords distance measure de dissimilarity between two vectors.

$$d(x,y) = \sum_{i=1}^{n} \left(\sqrt{x_i} - \sqrt{y_i}\right)^2 \quad (4)$$

### *Chi-Square Distance*

This distance is mainly used when dealing with qualitative variables.

$$d(x,y) = \sqrt{\sum_{i=1}^{n} \frac{(x_i - y_i)^2}{|x_i + y_i|}} \quad (5)$$

### *Chebychev distance or Queen-wise distance*

Chebychev distance is a particular case of Minkowsky distance where p=∞. It is a measure of dissimilarity.

$$d(x,y) = \max_{i=1}^{n} |x_i - y_i| \quad (6)$$

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### *Manhattan or city-block distance*

Manhattan distance is a particular case of Minkowski distance where p = 1. Manhattan distance is the distance between two points when a grid-like path is followed.

$$d(x,y) = \sum_{i=1}^{n} |x_i - y_i| \tag{7}$$

### *Mahalanobis distance*

Mahalanobis distance is based on the correlation between two variables.

$$d(x,y) = \sqrt{(x-y)^T C^{-1} (x-y)} \tag{8}$$

Where C is the covariance matrix.

### *Cosine distance*

It measures the degree of similarity of two vectors. His absolute value ranges from 0 to 1. When this value approaches 1, it means that the two vectors are getting closer. Commonly used in high-dimensional vector spaces for information retrieval and text mining.

$$\cos(\theta) = \frac{x.y}{\|x\|\|y\|} \tag{9}$$

### *CIE colorimetric color difference*

After creation of CIELAB, CIE 1976 $\Delta E^*_{ab}$ color-deference formulas have been defined based on Euclidian distance. In 1994 and 2001 the CIE94 $\Delta E^*_{94}$ and CIEDE $\Delta E^*_{00}$ formulas were published respectively to improve the first one [5].

In our work we focus our analysis on the two last color-difference metrics.

#### **CIE94 $\Delta E^*_{94}$**

The philosophy results from the fact that Lab color space is not totally uniform. So some weighting functions and parametric factors have been added to improve the first formula.

$$\Delta E^*_{94} = \sqrt{\left(\frac{\Delta L^*}{K_L S_L}\right)^2 + \left(\frac{\Delta C^*_{ab}}{K_C S_C}\right)^2 + \left(\frac{\Delta H^*_{ab}}{K_H S_H}\right)^2} \tag{10}$$

Where

$\Delta L^* = L^*_1 - L^*_2$

$\Delta a^* = a^*_1 - a^*_2$

$\Delta b^* = b^*_1 - b^*_2$

$C^*_i = \sqrt{a^{*2}_i + b^{*2}_i} \qquad i = 1,2$

$\Delta C^*_{ab} = C^*_1 - C^*_2$

$\Delta H^*_{ab} = \sqrt{\Delta a^{*2} + \Delta b^{*2} + \Delta C^{*2}_{ab}}$

$S_L = 1$,

$S_C = 1 + K_1 C^*_1$

$S_H = 1 + K_2 C^*_1$

$K_C = K_H = 1$ use to be unit.

The value of the weighting factors $K_L$, $K_1$, $K_2$ depend of the application

For graphic arts $K_L = 1$, $K_1 = 0.045$, $K_2$=0.015

For textiles KL = 2, K1 = 0.048, K2=0.014

#### **CIEDE $\Delta E^*00$**

Given two colors in Lab color space ($L_1$, $a^*_1$, $b^*_1$) and ($L_2$, $a^*_2$, $b^*_2$), we get the CIEDE $\Delta E^*_{00}$ color difference by:

$$\Delta E^*_{00} = \sqrt{\left(\frac{\Delta L'}{K_L S_L}\right)^2 + \left(\frac{\Delta C'_{ab}}{K_C S_C}\right)^2 + R_T \frac{\Delta C'_{ab}}{K_C S_C}\frac{\Delta H^*_{ab}}{K_H S_H}} \tag{11}$$

See details on steps to have the final result in [5].

## Experiments and results

Despite the drawbacks of RGB color space, we've decided to maintain images in RGB color space and then vary the distance metrics for image segmentation using K-mean algorithm. We compare the results obtained with the ones in Lab color space. In Lab space, the metrics used are colorimetric distances.

We've used matlab 7 and twenty images picked from Berkeley database [6]. For evaluation of the segmentation results we've used Levine and Nassif intra-region uniformity and inter-region contrast criteria.

The intra-region uniformity is inversely proportional to the variance of a considered feature values of the pixels belonging to a region.

The inter-region contrast is computed between adjacent regions. It is assumed that a uniform feature value of two adjacent regions is the average of the feature values of these regions. See detail of the computation in [7].

The following tables give the segmentation evaluation results. The first three tables give the results the segmentation evaluation using K-mean and different distance metrics. The last table shows segmentation evaluation results when the colorimetric color difference CIE94 and CIEDE00 are used.

For each image, the distance metric that provided the best segmentation score is boldfaced.

Recall that the smaller Levine and Nassif intra-region uniformity criterion score is, the better the segmentation result is. The higher Levine and Nassif inter-region contrast criterion score is, the better the segmentation result is.

Table 1: Segmentation score in RGB space

| | Euclidean | | Cityblock | | Cosine | |
|---|---|---|---|---|---|---|
| | intra | inter | Intra | inter | intra | inter |
| 3096 | 2.45 | 0.05 | 1.58 | 0.05 | 4.09 | 0.09 |
| 8023 | 4.29 | 0.04 | 3.90 | 0.04 | 14.42 | 0.02 |
| 12084 | 5.68 | 0.08 | 10.38 | 0.08 | 14.52 | 0.05 |
| 14037 | 5.02 | 0.12 | 3.12 | 0.12 | 7.42 | 0.18 |
| 16077 | 8.43 | 0.08 | 7.17 | 0.08 | 29.11 | 0.03 |
| 19021 | 5.84 | 0.11 | 5.88 | 0.11 | 22.64 | 0.08 |
| 21077 | 7.69 | 0.06 | 7.29 | 0.06 | 25.51 | 0.06 |
| 24077 | 7.23 | 0.08 | 8.30 | 0.09 | 24.20 | 0.09 |
| 33039 | 6.76 | 0.10 | 6.04 | 0.11 | 10.82 | 0.11 |
| 37073 | 9.34 | 0.05 | 3.79 | 0.05 | 19.68 | 0.05 |
| 38082 | 1.85 | 0.10 | 1.82 | 0.10 | 6.23 | 0.08 |
| 38092 | **4.99** | **0.07** | 5.71 | 0.08 | 52.46 | 0.04 |
| 41033 | 3.26 | 0.06 | 7.07 | 0.07 | 17.84 | 0.07 |
| 41069 | **3.44** | **0.07** | 5.89 | 0.07 | 21.30 | 0.05 |
| 42012 | 3.45 | 0.09 | 5.86 | 0.10 | 8.41 | 0.13 |
| 42049 | 4.71 | 0.04 | 4.84 | 0.04 | 20.16 | 0.08 |
| 43074 | 2.23 | 0.07 | 3.14 | 0.08 | 10.01 | 0.03 |
| 45096 | 9.39 | 0.14 | **5.79** | **0.13** | 19.17 | 0.16 |
| 54082 | 4.02 | 0.07 | 3.70 | 0.07 | 8.44 | 0.08 |
| 55073 | **5.40** | **0.13** | 6.75 | 0.13 | 19.82 | 0.15 |

Table 2: Segmentation score in RGB space

| | Chi-Square | | Minkowski_5 | | Mahalanobis | |
|---|---|---|---|---|---|---|
| | intra | inter | intra | inter | intra | inter |
| 3096 | 1.64 | 0.05 | 1.57 | 0.05 | 2.94 | 0.05 |
| 8023 | 4.05 | 0.04 | 4.03 | 0.04 | 8.51 | 0.03 |
| 12084 | 11.06 | 0.08 | **4.92** | **0.08** | 10.67 | 0.09 |
| 14037 | 3.07 | 0.14 | 5.00 | 0.11 | 8.06 | 0.13 |
| 16077 | 7.96 | 0.09 | 9.34 | 0.09 | 12.47 | 0.07 |
| 19021 | 10.84 | 0.11 | 13.15 | 0.12 | 14.17 | 0.11 |
| 21077 | 7.93 | 0.06 | **4.61** | **0.07** | 11.10 | 0.04 |
| 24077 | 7.84 | 0.08 | **6.61** | **0.08** | 23.66 | 0.09 |
| 33039 | 7.12 | 0.11 | 6.66 | 0.11 | 9.83 | 0.10 |
| 37073 | 5.24 | 0.06 | 3.58 | 0.08 | 14.04 | 0.05 |
| 38082 | 2.39 | 0.10 | 1.98 | 0.10 | 4.53 | 0.07 |
| 38092 | 7.48 | 0.08 | 7.68 | 0.08 | 22.44 | 0.04 |
| 41033 | 5.78 | 0.06 | 5.96 | 0.07 | 14.18 | 0.05 |
| 41069 | 5.98 | 0.07 | 6.35 | 0.07 | 12.72 | 0.05 |
| 42012 | 4.76 | 0.10 | 6.00 | 0.10 | 11.52 | 0.09 |
| 42049 | **4.41** | **0.04** | 5.84 | 0.04 | 11.21 | 0.05 |
| 43074 | 2.51 | 0.07 | **2.01** | **0.07** | 7.08 | 0.07 |
| 45096 | 8.60 | 0.12 | 8.45 | 0.10 | 24.95 | 0.22 |
| 54082 | 4.49 | 0.08 | 4.60 | 0.05 | 3.85 | 0.05 |
| 55073 | 6.60 | 0.13 | 5.50 | 0.12 | 13.80 | 0.09 |

Table 3: Segmentation score in RGB space

| | Queenwise | | Squarredchords | | Canberra | |
|---|---|---|---|---|---|---|
| | intra | inter | intra | inter | intra | inter |
| 3096 | 1.61 | 0.5 | **1.39** | **0.05** | 1.87 | 0.05 |
| 8023 | 4.25 | 0.04 | 4.53 | 0.04 | **3.65** | **0.04** |
| 12084 | 5.23 | 0.07 | 5.85 | 0.08 | 10.15 | 0.08 |
| 14037 | 4.38 | 0.11 | 3.42 | 0.15 | **2.95** | **0.12** |
| 16077 | 6.33 | 0.08 | **5.08** | **0.08** | 9.00 | 0.08 |
| 19021 | **4.36** | **0.10** | 6.43 | 0.11 | 9.11 | 0.11 |
| 21077 | 5.18 | 0.07 | 7.97 | 0.06 | 7.65 | 0.06 |
| 24077 | 7.58 | 0.09 | 7.39 | 0.08 | 7.55 | 0.08 |
| 33039 | 6.56 | 0.10 | 5.94 | 0.11 | **5.85** | **0.11** |
| 37073 | 3.80 | 0.07 | 9.67 | 0.06 | **2.87** | **0.06** |
| 38082 | 2.11 | 0.11 | **1.60** | **0.10** | 1.82 | 0.10 |
| 38092 | 5.93 | 0.08 | 5.08 | 0.07 | 5.35 | 0.07 |
| 41033 | **3.14** | **0.06** | 5.52 | 0.06 | 4.42 | 0.06 |
| 41069 | 3.60 | 0.07 | 3.68 | 0.07 | 3.61 | 0.07 |
| 42012 | **3.03** | **0.09** | 9.24 | 0.12 | 5.15 | 0.10 |
| 42049 | 6.5 | 0.04 | 4.71 | 0.04 | 4.58 | 0.04 |
| 43074 | 2.68 | 0.07 | 2.70 | 0.07 | 2.15 | 0.07 |
| 45096 | 14.67 | 0.10 | 12.27 | 0.12 | 8.75 | 0.12 |
| 54082 | 7.60 | 0.04 | 4.25 | 0.08 | **3.04** | **0.08** |
| 55073 | 5.47 | 0.11 | 6.13 | 0.13 | 5.93 | 0.13 |

Table 4: Segmentation score in Lab space

| | Euclidean | | $\Delta E^*_{94}$ | | $\Delta E^*_{00}$ | |
|---|---|---|---|---|---|---|
| | Intra | Inter | intra | inter | intra | inter |
| 3096 | **1.52** | **0.05** | 1.91 | 0.05 | 1.55 | 0.05 |
| 8023 | 4.30 | 0.04 | 3.36 | 0.04 | **3.35** | **0.04** |
| 12084 | **5.63** | **0.08** | 7.37 | 0.09 | 9.01 | 0.09 |
| 14037 | **3.6** | **0.14** | 4.25 | 0.12 | 5.94 | 0.16 |
| 16077 | 5.50 | 0.06 | 7.69 | 0.07 | **5.15** | **0.06** |
| 19021 | 7.56 | 0.10 | **6.88** | **0.11** | 11.42 | 0.11 |
| 21077 | **5.15** | **0.06** | 6.98 | 0.06 | 5.32 | 0.06 |
| 24077 | **6.41** | **0.07** | 10.00 | 0.09 | 11.03 | 0.08 |
| 33039 | 6.59 | 0.10 | 6.54 | 0.10 | **5.74** | **0.10** |
| 37073 | 9.63 | 0.05 | 4.65 | 0.05 | **3.71** | **0.06** |
| 38082 | 1.60 | 0.10 | **1.48** | **0.10** | 2.00 | 0.10 |
| 38092 | 5.00 | 0.06 | **4.35** | **0.06** | 4.41 | 0.07 |
| 41033 | 3.94 | 0.07 | **3.88** | **0.07** | 5.46 | 0.07 |
| 41069 | **3.48** | **0.07** | 3.58 | 0.06 | 3.56 | 0.06 |
| 42012 | **3.22** | **0.08** | 5.16 | 0.09 | 3.74 | 0.10 |
| 42049 | 4.41 | 0.04 | **4.20** | **0.04** | 4.36 | 0.04 |
| 43074 | 3.63 | 0.07 | 3.32 | 0.07 | **2.28** | **0.07** |
| 45096 | 8.60 | 0.14 | 8.87 | 0.12 | 11.84 | 0.14 |
| 54082 | 2.83 | 0.08 | 3.73 | 0.06 | **2.53** | **0.08** |
| 55073 | 6.55 | 0.13 | 8.27 | 0.12 | 8.64 | 0.13 |

## Discussion and conclusion

Only 7/20 of scores are better when we use the colorimetric difference metric in L*a*b* space.

The distance metrics squared chords, Canberra, Queenwise and Minskowsky 5 (p=5) give better results in RGB space.

Considering the sample of images on wish we work, Lab color space is not always the better color space for image segmentation. Better results are obtained in RGB color space with some distance metrics different from Euclidian distance. Depending to the image and the processing, we have to choose the more suitable color space and distance metric. Further experiments could be done to map image categories to most suitable distance metrics.

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