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Color Content-based Image Classification

Szabolcs Sergyán

Budapest Tech
sergyan.szabolcs@nik.bmf.hu

Abstract: In content-based image retrieval systems the most efficient and simple searches are the color-based searches, which can be realized in several color spaces and by several color descriptors. In this paper the possibility of image classification using certain color descriptors is examined, and the usage of different color spaces and descriptors depending on the image database domain is presented.

Keywords: Content-based image retrieval, Color spaces, Color descriptors, Clustering, Image classification

1 Introduction

The color has great importance in content-based image retrieval systems, which is stored in the intensity vectors of image pixels, and this information can be retrieved simply. However the color can be represented in differenct color spaces, and that is not irrelevant which color space is used in an application. The color information of an image represented in an arbitrary color space can be stored on several ways, but that is strongly application dependent which representation method is the most efficient at a determined search.

This paper wants to give an answer to that question, which color space or color feature representation is the most efficient to reveal the similarity of color images, if we want to define similarity by right of color, lightness and feeling of images. During this examination I ordered images into classes considering color space and color feature, and examined that, which classes are consistence [1] based on color, lightness or feeling.

Thie first part of Section 2 introduces the applied color spaces and conversion rules between them. The second part of Section 2 presents representation method of color features. Section 3 introduces the way of classification among images in the space of each color feature. Section 4 introduces the environment and the results of the fulfilled test. In Section 5 some possibilities of improvements are written.

2 Applied Color Spaces and Descriptors

This section presents the applied color spaces and color descriptors which were used in this paper and the connected tests. During the usage of these methods the [2] paper was considered.

2.1 Color Spaces

Digital representation of color images is realized by storage of color intensity values of each pixels. These intensity values usually are described by three dimensional vectors, whose components largely depend on the applied color space. The detailed description of color spaces can be found in [3].

2.1.1 RGB Color Space

RGB space is a widely used color space for image display. It is composed of three color components red, green and blue. Since color cameras, scanners and displays are most often provided with direct RGB signal input and output, this color space is the basic one, which is, if necessary, transformed into other color spaces.

2.1.2 RGB Color Space

In order to eliminate the influence of illumination intensity, color can be plotted on a two-dimensional diagram such as: $r+g+b=1$.

Tristimulus values are thus definied by:

$$r=\frac{R}{R+G+B},\quad g=\frac{G}{R+G+B},\quad b=\frac{B}{R+G+B} \tag{1}$$

where *R*, *G* and *B* the red, green and blue coordinates of one pixel in RGB space, and *r*, *g* and *b* the coorinates of the same pixel in rgb space, respectively.

The transformation from RGB space to rgb space a very simple color normalization method, whose advantage is the quick computation. We should use much more difficult normalization method as well, which remains in the RGB space, i.e. color cluster rotation [4].

2.1.3 CIE XYZ Color Space

In the CIE XYZ color space, the tristimulus values are not the *S* (short), *M* (middle), and *L* (long) stimuli of the human eye, but rather a set of tristimulus values called *X*, *Y*, and *Z*, which are also roughly red, green and blue, respectively. Two light sources may be made up of different mixtures of various colors, and yet have the same color. If two light sources have the same apparent color, then they will have the same tristimulus values, no matter what different mixtures of light were used to produce them.

In order to calculate *X*, *Y* and *Z* tristimulus values from *R*, *G* and *B* tristimulus values, the following system of equations have to be used:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \frac{1}{0.17697} \cdot \begin{bmatrix} 0.49 & 0.31 & 0.20 \\ 0.17697 & 0.81240 & 0.01063 \\ 0.00 & 0.01 & 0.99 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix}. \tag{2}$$

2.1.4 XYZ Color Space

The chromaticity coordinates x, y and z are obtained by taking the ratios of the tristimulus values to their sum.

$$x = \frac{X}{X+Y+Z}, \quad y = \frac{Y}{X+Y+Z}, \quad z = \frac{Z}{X+Y+Z} \tag{3}$$

Because $x + y + z = 1$, only two of three coordinates are needed to describe a color.

2.1.5 YCbCr Color Space

YCbCr is a family of color spaces used in video systems. *Y* is the luma component and *Cb* and *Cr* the blue and red chroma components.

The following equation shows the transfromation rule from RGB to YCbCr:

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \frac{1}{255} \cdot \left(\begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112 \\ 112 & -93.786 & -18.214 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \right). \tag{4}$$

2.1.6 HSV Color Space

HSV space is frequently used in computer graphics and is a rather intuitive way of describing color. The three color components are hue, saturation (lightness) and value (brightness). The hue is invariant to the changes in illumination and camera direction. RGB coordinates can be easily translated to the HSV coordinates by the following formula.

Let *H*, *S*, *V*, *R*, *G* and *B* denote the hue, saturation, value, reg, green and b components, respectively. $H \in [0,360)$ and the others are the elements of $[0,1]$.

$$H = \begin{cases} \text{undefined} & \text{if } \max(R,G,B) = \min(R,G,B) \\ \dfrac{60 \cdot (G-B)}{\max(R,G,B) - \min(R,G,B)} + 0 & \text{if } \max(R,G,B) = R \text{ and } G \geq B \\ \dfrac{60 \cdot (G-B)}{\max(R,G,B) - \min(R,G,B)} + 360 & \text{if } \max(R,G,B) = R \text{ and } G < B \\ \dfrac{60 \cdot (B-R)}{\max(R,G,B) - \min(R,G,B)} + 120 & \text{if } \max(R,G,B) = G \\ \dfrac{60 \cdot (R-G)}{\max(R,G,B) - \min(R,G,B)} + 240 & \text{if } \max(R,G,B) = B \end{cases} \tag{5}$$

$$S = \begin{cases} 0 & \text{if } \max(R,G,B) = 0 \\ 1 - \dfrac{\min(R,G,B)}{\max(R,G,B)} & \text{otherwise} \end{cases} \tag{6}$$

$$V = \max(R,G,B) \tag{7}$$

2.1.7 Opponent Color Space

The opponent color space uses opponent color axes (*R-G, 2B-R-G, R+G+B*). This representation has the advantage of isolating the brightness information on the third axis. With this solution, the first two chromaticity axes, which are invariant to the changes in illumination intensity and shadows, can be down-sampled since humans are more sensitive to brightness than they are to chromatic information.

2.2 Color-based Feature Vectors

In the following subsections, some commonly used color descriptors are introduced: the color moments, color histogram and color coherence vector.

2.2.1 Color Moments

The first order (mean), the second (variance) and the third order (skewness) color moments have been proved to be efficient and effective in representing color distribution of images [5].

The first three moments are defined as:

$$\mu_i = \frac{1}{N} \sum_{j=1}^{N} f_{ij} \tag{8}$$

$$\sigma_i = \sqrt{\frac{1}{N} \sum_{j=1}^{N} \left(f_{ij} - \mu_i\right)^2} \tag{9}$$

$$s_i = \sqrt[3]{\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij} - \mu_i\right)^3} \qquad (10)$$

where f_{ij} is the value of the *i*-th color component of the image pixel *j*, and *N* is the number of pixels in the image.

Since only 9 (three moments for each of the three color components) numbers are used to represent the color content of each image, color moments are a very compact representation compared to other color features. Due to this compactness, it may also lower the discrimination power.

2.2.2 Color Histogram

The color histogram is easy to compute and effective in characterizing both the global and local distribution of color in an image. In addition, it is robust to translation and rotation about the view axis and changes only slowly with the scale, occlusion and viewing angle.

Since any pixel in the image can be described by three components in a certain color space, a histogram, i.e., the distribution of the number of pixels for each quantized bin, can be defined for each component. Clearly, the more bins a color histogram contains, the more discrimination power it has. However, a histogram with a large number of bins will not only increase the computational cost, but will also be inappropriate for building efficient indexes for image databases.

2.2.3 Color Coherence Vector

In [6] a different way of incorporating spatial information into the color histogram, color coherence vector (CCV), was proposed. Each histogram bin is partioned into two types, i.e., coherent, if it belongs to a large uniformly-colored region, or incoherent, if it does not. Let α_i denote the number of coherent pixels in the *i*-th color bin and β_i denote the number of incoherent pixels in an image. Then, the CCV of the image is defined as the vector $\langle(\alpha_1,\beta_1),(\alpha_2,\beta_2),\ldots,(\alpha_N,\beta_N)\rangle$. Note that $\langle\alpha_1+\beta_1,\alpha_2+\beta_2,\ldots,\alpha_N+\beta_N\rangle$ is the color histogram of the image.

3 Cluster-based Classification Method

We generate all considered color descriptor in the 7 color spaces mentioned in Section 2. We do color moments for all color chanel in all mentioned color space. So thus three feature is obtained by chanel. Likewise color moments are considered for the three color chanels together, and in this way nine feature is achieved. During the preparation of histograms and color coherence vectors 64 bins were used, in each chanel 4 bins.

The images can be classified using the obtained 6 features (4 from moments, 1 from histogram and another one form CCV) per color space. For the classification the k-means clustering algorithm was used by k=4.

The substance of k-means clustering method is the following.

1 k points of n-dimensional space is selected randomly, and clusters are defined in that way, all points belong to the nearest selected point. (In this part of algorithm a distance measure is necessary.)

2 For each obtained cluster the mass center point is calculated, and further it will be considered as the center point of the cluster.

3 Each point belongs to the cluster of the nearest center point.

4 The algorith stops when the clusters are stables.

That is proved the steady state always sets, but that is not sure, it will be the possible best achievement, it may be only a 'locally' suitable result as well.

During clustering I used Euclidean distance measure among the feature vectors. In this way the clusters issued using the distance between 3, 9, 64 and 128 dimensional vectors in the case of moments per chanel, moments of all chanels, histograms and color coherence vectors, respectively.

4 Experiments

4.1 Experimental Environment

I used 136 images which were downloaded from the http://wikipedia.org site. Among the images were pictures, painted or drawn images, and landscapes, still-lifes, bills as well. So the domain of images can be considered very broad.

In these images I fulfilled the abovementioned classification method in 7 color spaces using 6 color features.

4.2 Experimental Results

The achievement of experiments is summarized in Table 1.

Color space	Color descriptor	Classification based on
RGB	Moments of R chanel	Lightness
XYZ	Moments of Z chanel	Lightness Blue color
xyz	Moments of x chanel	Red color
xyz	Moments of z chanel	Blue color
YCbCr	Moments of Y chanel	Lightness
YCbCr	Moments of Cb chanel	Blue color
YCbCr	Moments of Cr chanel	Red color
HSV	Moments of H chanel	Number of colors
HSV	Moments of S chanel	Sharp and blurred colors
HSV	Moments of V chanel	Lightness
Opponent space	Moments of 1. chanel	Blue and red color
Opponent space	Moments of 2. chanel	Blue color Sharp and blurred colors
RGB	Moments	Lightness, blue color
YCbCr	Moments	Lightness, blue color
HSV	Moments	Darkness, blue color
rgb	Histogram	Blue and green color
rgb	CCV	Lightness
xyz	CCV	Lightness Blue and green color
YCbCr	CCV	Blue color
Opponent space	CCV	Blue color

Table 1
Results of the experiments

In those cases, which were not mentioned in Table 1, did not issue such classes, which might be consistence from whatever point of view.

A surprising result of the experiments is that, the best classification is yielded by the moments and color coherence vectors, while in the similarity retrieval case frequently used histogram based classification did not prove suitable.

5 Further Works

The obtained achievements may be repaired, if other color descriptors ought to be tried in the representation of color features. Another improvement possibility, if for all objects of an image the color descriptors will be generated, and then applies the classification method.

A further improvement possibility may be a development of a user interface, where considering the user's feedback, the mistakes of the classification may be repaired. After the repaired classification the images can be ordered into hierarchy. In order to this some methods [8] are necessary which are frequently used in object oriented classification.

Conclusions

This paper introduced the most frequently used color spaces and color descriptors used in CBIR. Images were classified in different color spaces based on several color descriptors. I presented which color descriptor of which color space is suitable for several type of classification.

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