Color Moments

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Color moments are measures that can be used differentiate images based on their features of color. Once calculated, these moments provide a measurement for color similarity between images. These values of similarity can then be compared to the values of images indexed in a database for tasks like image retrieval.

The basis of color moments lays in the assumption that the distribution of color in an image can be interpreted as a probability distribution. Probability distributions are characterized by a number of unique moments (e.g. Normal distributions are differentiated by their mean and variance). It therefore follows that if the color in an image follows a certain probability distribution, the moments of that distribution can then be used as features to identify that image based on color.

Stricker and Orengo [1] use three central moments of a image's color distribution. They are Mean, Standard deviation and Skewness. A color can be defined by 3 or more values. (Here we will restrict ourselves to the HSV scheme of Hue, Saturation and brightness, although alternative encoding could just as easily be used.) Moments are calculated for each of these channels in an image. An image therefore is characterized by 9 moments - 3 moments for each 3 color channels. We will define the i-th color channel at the j-th image pixel as p_{ij} . The three color moments can then be defined as:

MOMENT 1 – Mean :

$$E_i=\sum_{N}^{j=1}\frac{1}{N}p_{ij}$$

Mean can be understood as the average color value in the image.

MOMENT 2 - Standard Deviation :

$$\sigma_i=\sqrt{\left(\frac{1}{N}\sum_{N}^{j=1}(p_{ij}-E_i)^2\right)}$$

The standard deviation is the square root of the variance of the distribution.

MOMENT 3 – Skewness :

$$s_i=\sqrt[3]{\left(\frac{1}{N}\sum_{N}^{j=1}(p_{ij}-E_i)^3\right)}$$

Skewness can be understood as a measure of the degree of asymmetry in the distribution.

A function of the similarity between two image distributions is defined as the sum of the weighted differences between the moments of the two distributions. Formally this is:

$$d_{mom}(H,I)=\sum_{i=1}^{r} w_{i1}\left|E_i^1-E_i^2\right|+w_{i2}\left|\sigma_i^1-\sigma_i^2\right|+w_{i3}\left|s_i^1-s_i^2\right|$$

Where:

(H,I)	: are the two image distributions being compared
i	: is the current channel index (e.g. 1 = H, 2 = S, 3 = V)
r	: is the number of channels (e.g. 3)
E_i^1, E_i^2	: are the first moments (mean) of the two image distributions
σ_i^1, σ_i^2	: are the second moments (std) of the two image distributions
s_i^1, s_i^2	: are the third moments (skewness) of the two image distributions
w_i	: are the weights for each moment (described below)

Pairs of images can be ranked based on their d_{mom} values. Those with greater values are ranked lower and considered less similar than those with a higher rank and lower d_{mom} values.

It should be noted that the d_{mom} value is a similarity function and not a metric. It is very possible that the comparison of two different pairs of distributions can result in the same d_{mom} value. In practice this leads to false positives being retrieved along with, hopefully, truly similar images. For an image retrieval system, this drawback is considered negligible.

w_i values are user specified weights. Depending on the application, or the condition of the images, these values can be tuned so that different preferences are given to different features of an image. For example, when using the HSV color space, the H value hue, which corresponds to the color type(e.g. red, green, blue), is often considered more relevant when judging perceived similarity than the V value, which corresponds to an image's brightness. We would therefore set w_{i1} higher for all i to penalize differences in average color. These weights can be likewise modified to increase or decrease the importance of other factors such as lighting conditions.

Example

To illustrate the concept we calculate color moments for the follow images and rank their similarity based on our results. Due to resource constraints, a larger database of images was unavailable for more rigorous proof of concept. However, for this, we refer the reader to the bibliography below.


Index Image


Test Image 1


Test Image 2

Step 1: Preformat Images (Not required)

We first scale all images to the same size: 320x240. This is done for this example's efficiency. Because color moments are based on probability distributions, image size should not change the result of comparison. In general, the larger the image, the greater the accuracy that can be achieved as a larger image will have more data points with which to define its distribution.

Step 2 : Calculate Moments for Index Image

We calculate the three color moments using the formula defined above for the ' Index Image'. The values are:

$$\begin{bmatrix} 0.1016 & 0.1149 & 0.1779 \\ 0.8583 & 0.1139 & 0.0563 \\ 0.6416 & 0.2994 & 0.0974 \end{bmatrix}$$

Index Image

Where the rows correspond to each of our moments and the columns to our channels.

Step 2: Calculate Moment for Other Query Images

We then repeat the calculations for our two test images. The values are:

$$\begin{bmatrix} 0.1718 & 0.0986 & 0..1400 \\ 0.7619 & 0.1508 & 0.0455 \\ 0.7062 & 0.2242 & 0.0772 \end{bmatrix} \qquad \begin{bmatrix} 0.1878 & 0.1671 & 0.2331 \\ 0.2462 & 0.2281 & 0.2492 \\ 0.6052 & 0.3532 & 0.1534 \end{bmatrix}$$

Test Image 1 Test Image 2

Step 3: Calculate DOM value

We use the following weight matrix to weight saturation slightly higher than hue or value:

$$\mathbf{W} = \begin{bmatrix} 1 & 2 & 1 \\ 1 & 2 & 1 \\ 1 & 2 & 1 \end{bmatrix}$$

We now calculate the d_{mom} value for $d_{mom}(Index, Test1)$ and $d_{mom}(Index, Test2)$. The following values result:

$$d_{mom}(Index, Test1) = 0.5878$$

$$d_{mom}(Index, Test2) = 1.5585$$

Step 4: Rank images based on similarity

As we can see from above, if we compare the two d_{mom} values:

$$d_{mom}(Index, Test1) < d_{mom}(Index, Test2)$$

We can therefore say that ' Test Image 1' is more similar to the 'Index Image' than ' Test Image 2' is to the ' Index Image', based on color moments. This result is what we would intuitively expect from perceived similarity.

Concluding Remarks

Color moments have proven [1] [4] [5] to be a successful technique for indexing images based on color. Their accuracy consitently outperforms [1] classic color indexing techniques such as color indexing [2] [3]and cumulative color histograms[1].

Bibliography

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