Block wise Color Moments

(BCM)

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Chapter 1

Introduction

The recent emergence of multimedia and the availability of large images have made content-based information retrieval an important research topic. The most frequently cited visual contents for image retrieval are colour, texture, and shape. Among them, the colour feature is most commonly used. It is robust to complex background and independent of image size and orientation.

The colour histogram is the best known colour feature and is used by the QBIC system. It is invariant to rotation, translation and scaling. To take into account similarities between similar but not identical colours, the QBIC system introduced the quadratic distance to measure the similarity between two histograms.

To overcome the quantisation effects of the colour histogram, Stricker and Orengo used colour moments as feature vectors for image retrieval. Since any colour distribution can be characterised by its moments, and most information is concentrated in the low-order moments, only the first moment (mean), the second moment (variance) and the third moment (skewness) are taken as features. The method is not appropriate for retrieving partially similar images.

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.

Chapter 2

Mathematical Formulation

Stricker and Orengo uses three central moments of a image's color distribution. They are Mean, Standard deviation and Skewness. Color can be defined by 3 or more values. Moments are calculated for each of these channels in an image. An image therefore is characterized by 9moments - 3 moments for each 3 color channels. We will define the i-th color channel at the j-th image pixel as pij.

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 distrib ution.

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

r : is the number of channels

Ei1,Ei2 : are the first moments (mean) of the two image distributions

σi1,σi2 : are the second moments (std) of the two image distributions

si1,si2 : are the third moments (skewness) of the two image distributions

wi : are the weights for each moment.

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.

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.

wi 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 wi1 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.

Chapter 3

Example:

To Understand the concept we calculate color moments for the follow images and rank their similarity based on our results.


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 Moment for Other Query Images

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

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

Index Image

Step 2: Calculate Moment for Other Query Images

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

$$\begin{bmatrix} 0.1718 & 0.0986 & 0..1400 \\ 0.7619 & 0.1508 & 0.0455 \\ 0.7062 & 0.2242 & 0.0772 \end{bmatrix}$$

Test Image 1

$$\begin{bmatrix} 0.1878 & 0.1671 & 0.2331 \\ 0.2462 & 0.2281 & 0.2492 \\ 0.6052 & 0.3532 & 0.1534 \end{bmatrix}$$

Test Image 2

Step 3: Calculate DOM value

We use the following weight matrix to weight saturation slightly high er 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.

Chapter 4

Learning Outcome

A new colour image retrieval method based on primitives of colour moments is proposed. First, an image is divided into several blocks. Then, the colour moments of all blocks are extracted and clustered into several classes based on a fast non-iterative clustering algorithm. The mean vector of each class is considered as a primitive of the image. All primitives are used as feature vectors. Then, a specially designed similarity measure is used to perform colour image retrieval. The proposed method, unlike other methods, contains the detail colour information of each important part in an image. Comparison with other methods reveals that for most types of image, the proposed method outperforms other methods using colour set, colour moments, colour correlograms, water-filling, wavelet moments, and the four MPEG-7 colour descriptors, as features.

Since each feature will be the most suitable for a particular kind of image, to utilise this phenomenon, a colour image retrieval system is also designed. It includes the proposed method and others using the abovementioned features. In this system, to meet the preferences of users, a relevance feedback algorithm is proposed to automatically determine the most appropriate feature, according to the user's response. The proposed system can be used as part of a digital library for content-based image retrieval (CBIR).

Appendix A

References

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