A Novel Image Retrieval Method Based on Color Autocorrelogram and Mutual Information

Xinning Shen, Xiaolong Wang, Jianhong Du
School of Information Science and Technology Fudan University, Shanghai, China
sxnfnj@hotmail.com, 11210720077@fudan.edu.cn

Abstract - This paper presents a novel color feature descriptor, namely Color Mutual Information (CMI), to solve the problems of high computational complexity and low retrieval accuracy among the existing methods. The new color feature vector which describes the global and spatial distribution relation among different colors is obtained by calculating the average mutual information between one color and all the colors around it in the color correlation feature matrix, thus reducing the computational complexity. Inter-feature normalization has been applied in the combination of Color Mutual Information and Color Autocorrelogram (CA) to enhance the retrieval accuracy. The experimental result show that, in the circumstance with either invariable illumination or variable illumination, the newly integrated algorithm Color Autocorrelogram and Mutual Information (CAMI) performs better in terms of computational complexity, real-time response speed and retrieval accuracy.

Index Terms - Image Retrieval, Color Feature, Color Correlation, Color Mutual Information, Feature Normalization.

I. Introduction

Content-Based Image Retrieval (CBIR), a technology that realizes information retrieval by using the image content directly, is currently a popular method in information retrieval. Google, Yahoo, Bing and Baidu have all launched image search engines taking the content of images as input. Since people focus more on the color, image retrieval methods based on color feature have been developing fast during the past decade.

Feature extraction is a preprocessing step for image indexing and retrieval in the CBIR system and several color description technologies have been proposed to be used as the feature vectors. Color Histogram is the earliest method to express the feature, which is invariant to rotational changes, distance changes and partial occlusion of the target object around the view [1]. However, Color Histogram only presents the global distribution of color and cannot provide the spatial correlation between different colors. Huang et al. proposed a new color image feature called the Color Correlogram (CC) and used it for image indexing and comparison [2]. Apart from the spatial correlation of colors, CC also describes the global distribution of local spatial correlation of colors. Experiments show that CC is a much more efficient approach for image retrieval, especially among the inquiry spaces with the same correlation. However, CC is an approach with relatively expensive computation due to its $O(m^2d)$ computational time. The authors also presented a spatial correlation between identical colors called Color Autocorrelogram with less computation time of $O(md)$ at the expense of the reduction of retrieval efficiency. Adam Williams and Peter Yoon developed a method called Joint Correlogram (JC) that extends the autocorrelogram by adding multiple image features (texture, gradient etc) in addition to color [3]. Though JC is somewhat better than other existing approaches, namely Color Histogram and Color Correlogram, its computational time and space requirements is also greater than other approaches. Anucha et al. proposed a technology based on the autocorrelogram, called Auto Color Correlogram and Correlation (ACCC), which combines the autocorrelogram and new RGB feature vectors [4]. However, the computational time and feature vector of ACCC are also much more demanding than CA.

II. Proposed Method

In this paper, we propose a new color feature for fast image indexing and retrieval called Color Autocorrelogram and Mutual Information. The method extracts Color Mutual Information from the color correlation feature matrix as a new feature descriptor and combines CMI with CA to generate a complex feature. The highlights of this complex feature are: (i) it includes the spatial correlation of different pairs of colors and identical pairs of colors; (ii) it can be used to describe the global distribution of local spatial correlation of colors; (iii) the computational time and feature vector space are much less expensive than previous methods.

A. Color Correlation Feature Matrix

Notation. Let I be an $n\times n$ image. (For simplicity, we assume that the image is square.) The colors in I are quantized into m bins $c_1, \ldots, c_m$.

For a pixel $p=(x,y)\in I$, let $I(p)$ denote is its color. Let $I_c=\{p \mid I(p)=c\}$. Thus, the notation $p\in I_c$ is synonymous with $p\in I, I(p)=c$. For pixels $p_1=(x_1,y_1)$, $p_2(x_2,y_2)$, we define $|p_1-p_2|=\max\{|x_1-x_2|,|y_1-y_2|\}$. We denote the set $\{1,2,\ldots,n\}$ by $[n]$.

Definitions. The histogram h of I is defined for $i\in[m]$ by

$$h_{c_i}(I)=n^2\cdot\Pr_{p\in I}[p\in I_{c_i}] \tag{1}$$

For any pixel in the image, $h_{c_i}(I)/n^2$ gives the probability that the color of the pixel is c_i.

Let a distance $d\in[n]$ be fixed a priori. Then the correlogram of I is defined for $i,j\in[m],k\in[d]$ as

$$\gamma_{c_i,c_j}^{(k)}(I) = \Pr_{p_1 \in I_{c_i}, p_2 \in I}[p_2 \in I_{c_j} \parallel p_1 - p_2 \mid = k] \qquad (2)$$

Given any pixel of color c_i in the image, $\gamma_{c_i,c_j}^{(k)}$ gives the probability that a pixel at distance k away from the given pixel is of color c_j. Note that the size of the correlogram is $O(m^2d)$. The autocorrelogram of I captures spatial correlation between identical colors only and is defined by

$$\alpha_c^{(k)}(I) = \gamma_{c,c}^{(k)}(I) \qquad (3)$$

This information is a subset of the correlogram and requires only $O(md)$ space [2].

Take m=64 for example, given the pixel distance $d=k$, we can get a 64×64 color correlogram feature matrix as follows:

$\gamma_{c_1,c_1}^{(k)}$	…	$\gamma_{c_1,c_j}^{(k)}$	…	$\gamma_{c_1,c_{64}}^{(k)}$
…	…	…	…	…
$\gamma_{c_i,c_1}^{(k)}$	…	$\gamma_{c_i,c_j}^{(k)}$	…	$\gamma_{c_i,c_{64}}^{(k)}$
…	…	…	…	…
$\gamma_{c_{64},c_1}^{(k)}$	…	$\gamma_{c_{64},c_j}^{(k)}$	…	$\gamma_{c_{64},c_{64}}^{(k)}$

The units $\gamma_{c_i,c_1}^{(k)}, \gamma_{c_i,c_2}^{(k)}, \ldots, \gamma_{c_i,c_{63}}^{(k)}, \gamma_{c_i,c_{64}}^{(k)}$ (i=1,2,…,64) in i-th row denote the probabilities that a pixel at distance k away from the given pixel c_i is color $c_1,\ldots,c_{64}$ in the image. It is easy to find the relationship:

$$\sum_{j=1}^{64} \gamma_{c_i,c_j}^{(k)} = 1, \ (i = 1,2,\ldots,64) \qquad (4)$$

Color Correlogram is an algorithm with an m×m feature vector. Despite the global distribution of local spatial correlation of colors, it takes a lot computation time and space for such large vectors.

Color Autocorrelogram only extracts the elements of the leading diagonal in the feature matrix to constitute the feature vector, which gives the spatial correlation of identical colors. In the example above, the feature vector of CA is $(\gamma_{c_1,c_1}^{(k)},\ldots\gamma_{c_i,c_i}^{(k)},\ldots,\gamma_{c_{64},c_{64}}^{(k)})$, whose size is far smaller than that of CC.

Computation. To compute the correlogram, it suffices to compute the flowing count (similar to the co-occurrence matrix in [5] for texture analysis of gray images)

$$\Gamma_{c_i,c_j}^{(k)}(I) = |\{p_1 \in I_{c_i}, p_2 \in I_{c_j} \parallel p_1 - p_2 \mid = k\}| \qquad (5)$$

for, $\gamma_{c_i,c_j}^{(k)}(I) = \Gamma_{c_i,c_j}^{(k)}(I)/(h_{c_i}(I) \cdot 8k)$. The denominator is the total number of pixel at distance k from any pixel of color c_i. The algorithm would consider each $p_1 \in I$ of color c_i and for each $k \in [d]$, count all $p_2 \in I$ of color c_j with $| p_1 - p_2 \mid = k$.

B. Color Mutual Information

Though Color Correlogram expresses different pairs of colors in the spatial distribution, its usage has been limited by large feature vectors in dealing with image matching. Simplified Color Autocorrelogram sharply reduces the computational complexity, yet the retrieval efficiency of the image with affluent colors or dramatic change in colors is not very good because only identical pairs of colors have been considered. We proposed Color Mutual Information based on the Color Correlogram feature matrix, which not only reduces the feature vector to m×1 but also introduces spatial information of different pairs of colors.

Mutual information was firstly advanced in the Information Theory [6]. It is a measurement of the information that the occurrence of an incident $Y=y_i$ provides for the occurrence of another incident $X=x_i$. It is defined as

$$I(x_i; y_i) = \log_2 \frac{p(x_i \mid y_i)}{p(x_i)} \qquad (6)$$

$I(x_i; y_i)$ is defined as the mutual information of x_i and y_i.

Likewise, Color Correlogram expresses how the spatial correlation of pairs of colors changes with distance. The element in the correlogram matrix denotes the occurrence probability of every pair of colors and each row of the matrix denotes the occurrence probabilities that assigned color c_i pairs with other colors. We define the color mutual information as the information that the occurrence of assigned color $C=c_i$ provides for the occurrence of other color $C=c_j$:

$$I(c_j; c_i) = \log_2 \frac{p(c_j \mid c_i)}{p(c_j)} = \log_2 \frac{\gamma_{c_i,c_j}^{(k)}}{p(c_j)} \qquad (7)$$

$\gamma_{c_i,c_j}^{(k)}$ is the corresponding element in the color correlogram matrix. We calculate the average information that the occurrence of assigned color $C=c_i$ provides for occurrence of all the colors surrounding c_i, and thus we have the average information between color $C=c_i$ and all the other colors:

$$I(C; c_i) = \sum_{j=1} I(c_j; c_i) p(c_j \mid c_i) \qquad (8)$$

Thus,

$$\begin{aligned} I(C; c_i) &= \sum_{j=1}^{m} (\log_2 \frac{\gamma_{c_i,c_j}^{(k)}}{p(c_j)}) \gamma_{c_i,c_j}^{(k)} \\ &= \sum_{j=1}^{m} [\gamma_{c_i,c_j}^{(k)} \log_2 \gamma_{c_i,c_j}^{(k)} - \gamma_{c_i,c_j}^{(k)} \log_2 p(c_j)] \end{aligned} \qquad (9)$$

$p(c_j)$ denotes the normalized color histogram of c_j after being quantified.

In the example of a 64×64 color correlogram feature matrix, after being transformed using the procedure above, we can get a 64×1 color mutual information feature vector within each pixel distance ($d=k$) from the color correlogram feature matrix.

III. Visual Similarity Measure

The type of similarity measure to be considered depends on the technique used for feature extraction. The L_1 and L_2 norm are commonly used distance metrics when comparing feature vectors of two images. In this paper the L_1 norm is used because it is simple and robust. Let f denote the feature vector (CA's feature vector or CMI's feature vector), the similarity of two images *I* and *I'* with the same number of color bins m and distance k is calculated as

$$D_{(I,I')} = dist(f_I - f_{I'}) = \sum_{k\in[d]} \frac{|f^{(k)}(I)-f^{(k)}(I')|}{1+f^{(k)}(I)+f^{(k)}(I')} \qquad (10)$$

A. Inter-feature Normalization

In this paper, we use the complex algorithm Color Autocorrelogram and Mutual Information to extract the similarity of images. The complex feature vector is the combination of CA's feature vector and CMI's feature vector. When we use the two kind of feature vectors to calculate the feature distance of two images respectively, the results of the heterogeneous features need to be normalized into the same scale and range [0,1] before feature fusion. The following inter-feature normalization process is used for each feature vector f_i [7].

1. In the image dataset (*N* images), for any pair of images I_i and I_j, compute the similarity distance $D(i, j)$ between them.

   $$D_{(i,j)} = dist(f_{I_i}, f_{I_j}), \quad (i, j = 1,2,...,N; i \neq j) \quad (11)$$

   Where f_{I_i} and f_{I_j} are the feature representations of images I_i and I_j.
2. For the $C_N^2 = \frac{N\times(N-1)}{2}$ possible distance values between any pair of images, treat them as a value sequence and find the mean *m* and standard deviation σ.
3. After a query *Q* is presented, compute the raw (unnormalized) similarity value between *Q* and the images in the database. Let $s_1,...,s_N$ denote the raw similarity values.
4. Normalize the raw similarity values as follows:

   $$s'_i = \frac{s_i - m}{3\sigma} \qquad (12)$$

   This Gaussian normalization will ensure 99% of s'_i to be within the range of [-1,1]. An additional shift will guarantee that 99% of similarity values are within [0,1]:

   $$s''_i = \frac{s'_i + 1}{2} \qquad (13)$$

   After this shift, in practice, we can consider all the values are within the range of [0,1], since an image whose distance from the query is greater than 1 is very dissimilar and can be considered to be at a distance of 1 without affecting retrieval.

B. Feature Fusion

After the inter-feature normalization, the features within a composite query are of equal weights. Let d_{Fi}, d_{Fj} denote the distance between two images after normalization, and the new similarity distance is defined as:

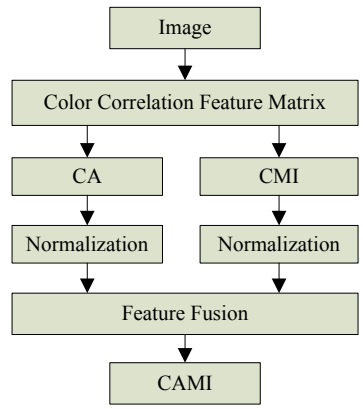

Fig.1 The flowchart of feature extraction and fusion

$$d_F = \lambda d_{Fi} + (1-\lambda) d_{Fj}, \quad \lambda \in [0,1] \qquad (14)$$

Where λ is the similarity weighting constant of CA and CMI. The smaller d_F is, the more similar the two images are.

Fig.1 shows the flow of our approach in details.

IV. Experiment and Evaluation

To evaluate the performance of CAMI, we designed two experiments, one in the circumstance with invariable illumination and another with variable illumination.

In the first experiment, we built an image database of 11100 color JPEG images with a size of 128×96 pixels and invariable illumination, including 9908 images from Corel, 1000 images from video frames and 192 images from the web. We randomly selected 100 images from the database as the query images which had 10 images analogous to them. Sixty-four colors and {1,3,5,7} for spatial distance were used in the computation of CA, ACCC, CAMI algorithms in this experiment. For CAMI, we used the distance metrics presented in section 3 for comparing feature vectors and the weighting constant λ for feature fusion was 0.5.

The metrics that we used for measuring the accuracy of queries are recall and precision, where recall is the fraction of the relevant images which have been retrieved, while precision is the fraction of the retrieved images which are relevant [8].

From the results shown in Table 1 and Fig.2, we can see that although CAMI consumes a little more retrieval time than CA, it has saved 17% of processing time compared to ACCC and it has much better performance in retrieval precision than CA and ACCC. Especially in the range of recall [0.4, 0.7], the precision of CAMI is 8%-10% higher than that of CA and ACCC.

Fig.3 shows the result of the first experiment, the image in the first column is the query image and the result is ranked from left to right in each line.

Table 1 Comparison for Feature Vector Size and Retrieval Time

Algorithms	Feature Vector	Size	Retrieval Time (100 images)
CA	Color Autocorrelogram	64×1	11.496s
ACCC	Color Autocorrelogram+ RGB average	64×4	15.725s
CAMI	Color Autocorrelogram+ Mutual Information	64×2	13.057s

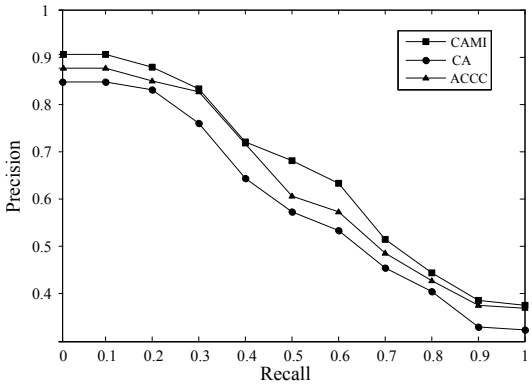

Fig.2 The average precision versus recall at 11 standard levels

Fig.3 The examples of resulting images from query image based on CAMI algorithm, the first column is original image.

In the second experiment, we built a database with 220 images, including 20 kinds of objects under 11 different illuminations, as shown in Fig.4. We used three methods m1m2m3 [9], Histogram Equalization (HE) [10] and Comprehensive Color Image Normalization (CCIN) [11] to remove the interference of illumination and CA, ACCC, CAMI for the retrieval after preprocessing. At last, we used Average Normalized Modified Retrieval Rank (ANMRR) as retrieval performance metrics [12]. The lower the ANMRR, the better the retrieval performance.

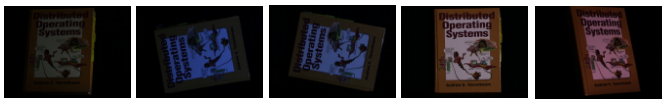

Fig.4 sample of image database with variable illumination

Table 2 Comparison for Feature Vector Size and Retrieval Time

	m1m2m3	HE	CCIN
CA	0.1527	0.7004	0.5682
ACCC	0.1024	0.6667	0.6344
CAMI	0.0931	0.6316	0.5589

The data in table 2 prove that no matter what kind of preprocessing is used to remove the illumination, CAMI has the best results out of all image retrieval methods.

5. Conclusions

In this paper, we propose a novel color descriptor Color Mutual Information and combine it with autocorrelogram. The new retrieval method CAMI not only overcomes the deficiency of the CA algorithms, but also reduces the computation complexity and retrieval time, enhances the retrieval precision and can be used as a real-time retrieval method. Experiments show that this method has better performance both with invariable illumination and variable illumination and is robust even in the presence of changes in scale, rotation and perspective.

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