

Spatial Color Indexing using ACC Algorithm

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Abstract—This paper presents a fast and robust color indexing techniques, namely auto color correlation (ACC) based on a color correlogram (CC), for extracting and indexing low-level features of images. The proposed technique can reduce computational time of color correlogram technique from $O(m^2d)$ to $O(md)$. Additionally, an extended technique of ACC based on the autocorrelogram, namely Auto Color Correlogram and Correlation (ACCC) is proposed. It is the integration of Autocorrelogram and Auto Color Correlation techniques that the computational time of ACCC is still $O(md)$. The experimental result show, the ACCC algorithm has the better efficiency than the AC algorithms for retrieving images. Moreover, the proposed method consumes less processing time than the CC algorithm so that the proposed method is applicable in practice for real-time processing.

Keywords—Image Retrieval, CBIR Systems, Feature Extraction, ACC, ACCC

I. INTRODUCTION

Content-Based Image Retrieval (CBIR) or Content-Based Visual Information Retrieval (CBVIR) is a computer vision application that automatically retrieves images based on their visual content. It has been an ongoing area of research for over 20 years. Most of the popular, commercial search engines, such as Google, Yahoo, and even the latest application, namely Bing, introduced by Microsoft, exploit pure keyword features for the retrieval process. However, they indicate an interest in applying the visual content of images as a part of developing an image search function. In currently, the CBIR systems presented in academic and research papers tend to focus on semantic level to retrieving images. However, an efficient color descriptor technique for image feature extraction is still required to extraction and indexing images. The technique, namely color correlogram, is widely used for finding the spatial correlation of each color in an image. It was introduced by Huang J. et al. The technique was implemented and it was found that the retrieval performance of a color correlogram was better than the standard color histogram and the color

coherence vector methods [3]. A color correlogram is a table indexed by color pairs, where the k -th entry for (i, j) specifies the probability of finding a pixel of color C_j at a distance k from a pixel of color C_i in the image. However, the color correlogram is expensive to compute and the computation time of the correlogram is $O(m^2d)$. Several authors also present a technique that captures the spatial correlation between identical colors called an autocorrelogram with a computation time of $O(md)$. However, an autocorrelogram only captures the distribution of each color in the image. The disadvantages are: 1) the color correlogram has computation complexity, and 2) the auto correlogram mainly captures the distribution of each color in the images. They mainly capture spatial information of the colors. In this paper, the correlogram technique is extended to improve the speed and efficiency of color indexing for an on-line CBIR system. Fig. 3 presents the major problems of the autocorrelogram technique.

An important question related to the limitations of a CBIR system is “How can we have a mathematical representation without loss of information for the general category of all images” [5]. The two pictures above show one of several problems related to this issue. The probability values of each color that are found by using the autocorrelogram mechanism are equal but in terms of the color correlation they are different, (see the Fig. 1).

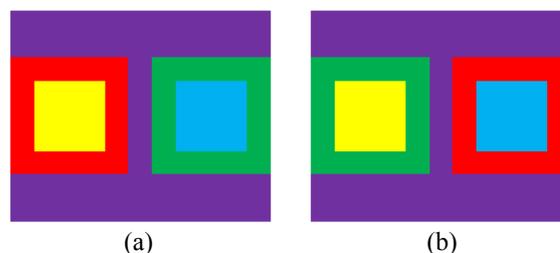


Fig. 1 Sample images: image a (left) and image b (right)

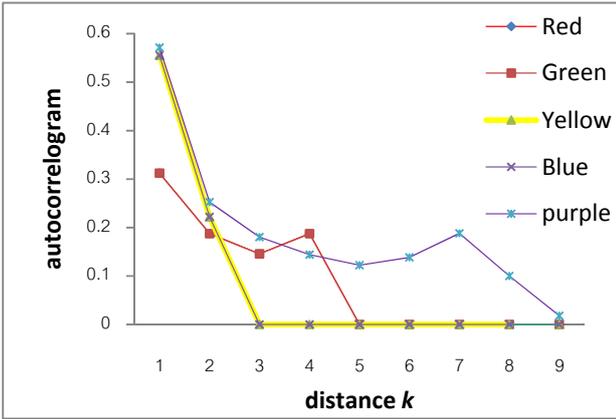


Fig. 2 Autocorrelogram of two sample images (from Fig. 1)

When we measure the similarity of the two pictures, these pictures are the same. However, you can use the color correlogram technique to solve this problem. This paper presents an efficient spatial color descriptor for image retrieval based on the correlogram technique that improves the disadvantages of the color correlogram and the autocorrelogram approaches. It can reduce computational time from $O(m^2d)$ to $O(md)$ when compared with several existing algorithms such as color correlogram.

This paper is organized as follows. Section II reviews related work. Section III proposes an advanced color image indexing technique. Section IV discusses experimental results in term of the efficiency of the ACC algorithm. Section V provides a summary and conclusion

II. RELATED WORK

Feature extraction is a preprocessing step for image indexing in CBIR systems. There are various visual descriptors used to extract a low-level feature vector of an image. However, in this paper, we focus on color descriptors for retrieving images. Although, several color description techniques have been proposed [2], [4], [9], they can be grouped into two classes based on whether or not they encode information related to the color spatial distribution. Examples of descriptors that do not include spatial color distribution include Color Histogram and Color Moments. Swain and Ballard were among the first who purposed the color histogram for object identification [4]. It is the most commonly used descriptor in image retrieval. Given a discrete color space defined by some color axes (e.g. red, green, blue), the color histogram is obtained by counting the number of times each color occurs in the image array. Examples of color descriptors that incorporate color spatial distribution methods include Color Coherence Vector (CCV) [1], Border/Interior Pixel Classification (BIC) [6], and Color Correlogram [3]. The CCV method uses a histogram-based method for comparing images that incorporate spatial information. The approach classifies each pixel in a given color bucket as coherent or incoherent, based on whether or not it is part of a large similarly-colored region and then uses a color coherence

vector (CCV) to store the number of coherent versus incoherent pixels with each color by separating coherent pixels from incoherent pixels.

CCV's provides finer distinctions than color histograms. Yi Tao and William I. Grosky [7] purposed a novel approach for spatial color indexing by using Delaunay triangulation, called a color anglogram. They used the HSI color model for image representation. In order to compute the color anglogram of an image, they first divide the image evenly into a number of $M*N$ non-overlapping blocks. The feature point is labeled with its spatial location, dominant hue, and dominant saturation. For each set of feature points labeled with the same hue or saturation, they construct a Delaunay triangulation and then compute the feature point histogram by discretizing and counting the two largest angles produced by this triangulation. Hang et al [3] proposed a new color image feature called the color correlogram and used it for image indexing and comparison. The main aspects of this image feature are: 1) it includes the spatial correlation of colors; 2) it can be used to describe the global distribution of local spatial correlation of colors; 3) it is easy to compute, and 4) the size of the feature result is relatively small. However, the color correlogram is an expensive computation resulting in a computational time of $O(m^2d)$. They also presented a spatial correlation between identical colors called an autocorrelogram with computation time of $O(md)$. Adam Williams and Peter Yoon [8] developed a joint correlogram that extends the autocorrelogram by adding multiple image features in addition to color. The joint correlogram technique is similar in spirit to the joint histogram [1]. The difference is that the correlogram includes spatial information about the image features in addition to global information about the features. The result of an experiment comparing these techniques shows that the joint correlogram is somewhat better than other existing approaches, namely, color histogram, joint histogram, and color correlogram but its time and space requirements in the joint correlogram also increased more than other approaches.

III. THE PROPOSED EFFICIENT SPATIAL COLOR DESCRIPTOR

In this section, we present an efficient algorithm that is an extension of the correlogram technique for color indexing. An auto color correlation expresses how to compute the mean color of all pixels of color C_j at a distance k -th from a pixel of color C_i in the image. Formally, the ACC of image $\{I(x,y), x = 1, 2, \dots, M, y = 1, 2, \dots, N\}$ is defined as

$$\begin{aligned}
 ACC(i,j,k) &= Avg V_{C_i V_{C_j}}^{(k)}(I) \\
 &= \{Avg V_{C_i V_{C_1}}^{(k)}(I), Avg V_{C_i V_{C_2}}^{(k)}(I), Avg V_{C_i V_{C_3}}^{(k)}(I) \mid c_1 \neq c_j\}
 \end{aligned} \tag{1}$$

Where the original image $I(x,y)$ is quantized to m colors C_1, C_2, \dots, C_m and the distance between two pixels $k \in [\min\{M, N\}]$ is fixed a priori. Let V_{C_j} is the RGB value of

color m in an image I . The mean colors are computed as follows:

$$Avg Y_{c_i, c_j}^{(k)}(I) = \frac{\Gamma_{c_i, c_j}^{(k)}(I)}{\Gamma_{c_i, c_j}^{(k)}(I)} \mid c_i \neq c_j$$

$$Avg Y_{c_i, c_j}^{(k)}(I) = \frac{\Gamma_{c_i, c_j}^{(k)}(I)}{\Gamma_{c_i, c_j}^{(k)}(I)} \mid c_i \neq c_j$$

$$Avg Y_{c_i, c_j}^{(k)}(I) = \frac{\Gamma_{c_i, c_j}^{(k)}(I)}{\Gamma_{c_i, c_j}^{(k)}(I)} \mid c_i \neq c_j \quad (2)$$

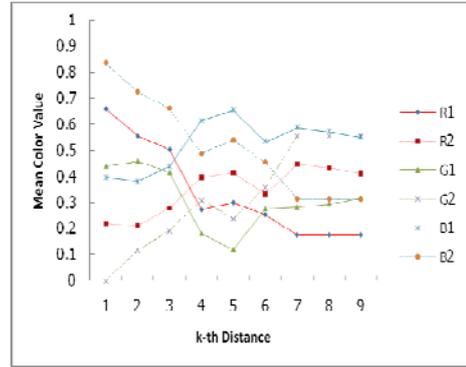
In order to gain a deeper understanding of the ACC's computational procedure, it is described as follows.

Algorithm: Auto Color Correlation

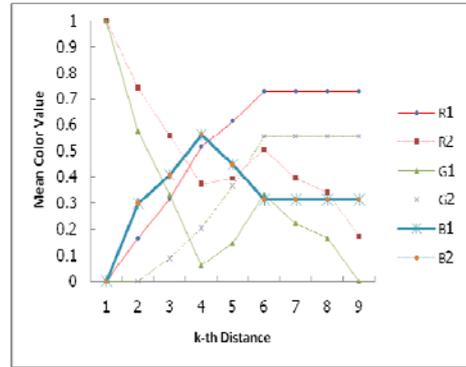
```

For every K distance {
  For every X position
    For every Y position {
      Ci ← current pixel
      While (Cj ← Get neighbors pixel of Ci at distance K) {
        For every color Cm {
          If (Cm = Ci and Ci ≠ Cj) {
            countColor++
            colorR[Cm] = colorR[Cm] + colorRCi
            colorG[Cm] = colorG[Cm] + colorGCi
            colorB[Cm] = colorB[Cm] + colorBCi
          }
        }
      }
    }
  }
  meanColorR = sum ( colorR[Cm] ) / countColor
  meanColorG = sum ( colorG[Cm] ) / countColor
  meanColorB = sum ( colorB[Cm] ) / countColor
}
    
```

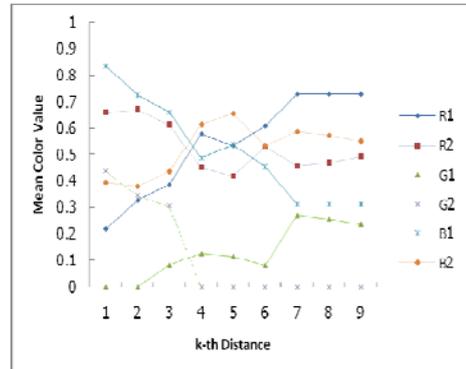
Consider the two sample images from Fig. 3, the auto color correlation corresponding to these images is shown in Fig. 5.



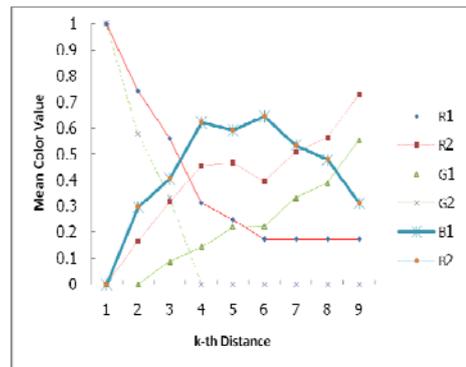
(a) Red



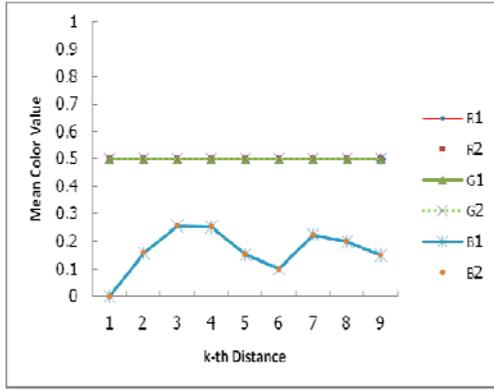
(b) Blue



(c) Green



(d) Yellow



(e) Purple

Fig. 3 The mean color of RGB space of two sample images (from Fig. 1)

If we consider only the background color of the images, the mean colors of RGB space are equal, but they are different if we consider all the colors of the images.

A. Auto Color Correlogram and Correlation (ACCC)

Although ACC is able to find the local spatial correlation between colors by reducing the size of color correlogram from $O(m^2d)$ to $O(md)$, it does not consider the color distribution values of each color in an image. Autocorrelogram is an efficient algorithm to solve this problem. Thus, we propose an extended technique of ACC based on the autocorrelogram, namely Auto Color Correlogram and Correlation (ACCC). It is the integration of Autocorrelogram and Auto Color Correlation techniques. However, we can compute the color distribution values and color correlation values concurrently. The size of ACCC is still $O(md)$. This expresses how to immediately capture the spatial correlation and distribution of each color in the image. It not only captures the spatial correlation between identical colors but also computes the local spatial correlation between colors. Using this proposed technique, the correlation values of colors for each color distribution of an image are computed efficiently. The Auto Color Correlogram and Correlation is defined as

$$ACCC(g, j, k) = \{ \gamma_{c_i}^{(k)}(I), Avg \gamma_{c_i, c_j}^{(k)}(I) \} \quad (3)$$

The images shown in Fig. 4 are used for presenting the underlying concept of each technique.

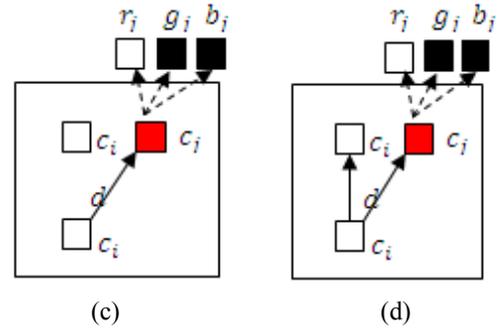
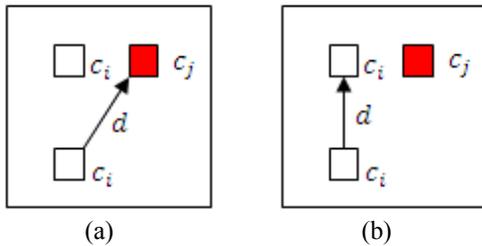


Fig. 4 The conceptual basis of the algorithms (a) color correlogram, (b) autocorrelogram, (c) auto color correlation, and (d) auto color correlogram and correlation

B. 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 [3]. The current section presents similarity measures for the proposed color descriptor in the case of image retrieval.

1) Similarity Measure for ACC

Two images I, I' can be compared using their ACC's, by using the L_1 distance. The similarity of correlogram feature vectors with the same number of k and m is calculated as

$$d(I, I') = \sum_{\forall i, j, k} \frac{|\gamma_{c_i, c_j}^{(k)}(I) - \gamma_{c_i, c_j}^{(k)}(I')|}{1 + \gamma_{c_i, c_j}^{(k)}(I) + \gamma_{c_i, c_j}^{(k)}(I')} \quad (4)$$

Based on the above similarity measures, the distance metrics of ACC is represented as

$$d(I, I') = \sum_{\forall i, j, k} \frac{|Avg \gamma_{c_i, c_j}^{(k)}(I) - Avg \gamma_{c_i, c_j}^{(k)}(I')|}{1 + Avg \gamma_{c_i, c_j}^{(k)}(I) + Avg \gamma_{c_i, c_j}^{(k)}(I')} \quad (5)$$

2) Distance Measure for ACCC

Let the ACCC pairs for the m color bin be (α_i, β_i) in I and (α'_i, β'_i) in I' . The similarity of the images is measured as the distances between the AC's and ACC's $d(I, I')$ and is applied from [2] as follows:

$$d(I, I') = \lambda_1 \sum_{\forall i} \frac{|\alpha_i - \alpha'_i|}{1 + \alpha_i + \alpha'_i} + \lambda_2 \sum_{\forall i} \frac{|\beta_i - \beta'_i|}{1 + \beta_i + \beta'_i} \quad (6)$$

Where λ_1 and λ_2 are the similarity weighting constants of autocorrelogram and auto color correlation, respectively. In the experiments conducted, $\lambda_1 = 0.5$ and $\lambda_2 = 0.5$. α_i and β_i are defined as follows:

$$\alpha_i = \gamma_{c_i}^{(k)}(I)$$

$$\beta_i = \{ Avg \gamma_{c_i, c_j}^{(k)}(I), Avg \gamma_{c_i, c_j}^{(k)}(I), Avg \gamma_{c_i, c_j}^{(k)}(I) \mid c_i \neq c_j \}$$

Note that the two descriptors, AC and ACC given different value ranges. The value 1 in the denominator is added to prevent division by zero but may not be suitable for AC's, the range of AC's is 0 to 1.

IV. EXPERIMENT AND EVALUATION

To evaluate the efficiency of the ACC and ACCC algorithms, they were tested on a database of 20,024 color JPEG and BMP images with a size of 140 x 100 pixels. This included 10,000 images randomly selected for downloading from the online Yahoo database with various keywords in various categories such as sunsets, animals, beaches, mountains, landscapes, building etc. and 10,024 images from Corel stock photographs. The heterogeneous image database is therefore very realistic and was utilized to evaluate various methods. We used the distance metrics that were presented in section IV for comparing feature vectors. Sixty-four colors and {1, 3, 5, 7, 9} for spatial distance were used in the computation of all algorithms in this experiment. 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 [10]. Let |R| be the number of relevant images for query q. Assume that an example request q generates an image answer. Let |A| be the number of images in this set. Further, let |R_a| be the number of relevant images in the answer set, the intersection of the sets R and A. The recall and precision measures are defined as follows.

$$\begin{aligned}
 \text{Recall} &= \frac{|R_a|}{|R|} \\
 \text{Precision} &= \frac{|R_a|}{|A|}
 \end{aligned}
 \tag{7}$$

Further, to evaluate the retrieval performance of our algorithms over all test queries based on the ranking of relevant images, precision versus recall is considered with the average precision at the recall level r being used [10]. Let N_q be the number of queries used. The average precision is defined as:

$$\text{Avg } P(r) = \sum_{i=1}^{N_q} \frac{P_i(r)}{N_q}
 \tag{8}$$

Where P_i(r) is the precision at recall level r for i-th query, the result is shown in Fig. 5.

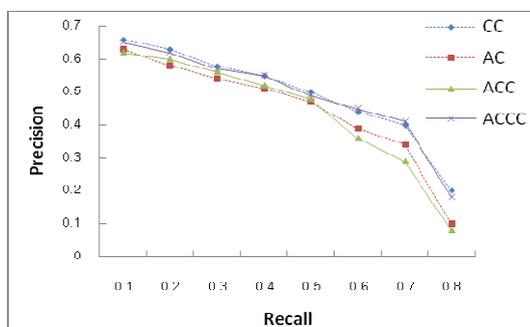


Fig. 5 The average precision versus recall at 11 standard levels for four distinct retrieval algorithms

From the experimental results shown in Fig. 5 and Table I, the AC algorithm has the same efficiency as the ACC algorithms for retrieving images. Moreover, the proposed method consumes less processing time than the CC algorithm so that the proposed method is applicable in practice for real-time processing.

Table I Comparison of other color descriptors

Methods	Average Recall	Average Precision
Color Correlogram	0.28	0.89
Autocorrelogram	0.23	0.82
Auto Color Correlation	0.24	0.81
Auto Color Correlogram Correlation	0.26	0.87

V. CONCLUSIONS

This research presents a fast and robust color indexing for CBIR systems. The goal was to reduce the computational time of color correlogram technique but remain strong efficiency. The advanced spatial color descriptors, namely; auto color correlation (ACC) and auto color correlogram and correlation (ACCC), are proposed. The precision versus recall measures are used to evaluate the performance of image retrieval compared to existing color descriptor algorithms such as color correlogram and autocorrelogram. The color descriptor improves the accuracy of retrieving images and reduces the computational time from O(m²d) to O(md).

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