ABSTRACT

Content-based image retrieval is the retrieval of images based on visual features such as colour, texture and shape. Current approaches to CBIR differ in terms of which image features are extracted; recent work deals with combination of distances or scores from different and usually independent representations in an attempt to induce high level semantics from the low level descriptors of the images. Content-based image retrieval has many application areas such as, education, commerce, military, searching, commerce, and biomedicine and Web image classification. This paper proposes a new image retrieval system, which uses color and geometric moment feature to form the feature vectors. Bhattacharyya distance and histogram intersection are used to perform feature matching. This framework integrates the color histogram which represents the global feature and geometric moment as local descriptor to enhance the retrieval results. The proposed technique is proper for precisely retrieving images even in deformation cases such as geometric deformations and noise. It is tested on a standard the results shows that a combination of our approach as a local image descriptor with other global descriptors outperforms other approaches.

INTRODUCTION

Content-based image retrieval measures the visual similarity between a query image and database images. The retrieval result is an images list ranked by their similarities with the query image. By extracting the feature vectors of the query image and the database images, there is need to develop similarity measures that will rank the database images by the actual distance between their vectors and the query image vector. Content Based Image Retrieval systems think that the best retrieving images are the most visually similar images to a given query image from a large collection of images. It is index visual characteristics of an image, such as its color, textures and shape to look for an explicit image in a large amount of images [1]. A similarity measure computed from the extracted features is used to rank the retrieved results. Several similarity measures have been introduced; such measures can be categorized as vector based measures that treats features as vectors, region based and global based or a combination of both, fuzzy or deterministic similarity measures, and the use of supervised, semi-supervised, or unsupervised learning. Sural, S. Gang Qian Pramanik, S. [2] analyzed the properties of the HSV (Hue, Saturation and Value) color space with emphasis on the visual perception of the variation in Hue, Saturation and Intensity values of an image pixel. HSV is a widely adopted color space [3-4]. A limitation of HSV color space was that dark colors were insensitive to saturation and hue changes and, similarly, the hue value was negligible for low saturation colors. MIRROR [5] image retrieval systems Investigate MPEG7 visual descriptors. The MPEG-7 standard [6] provided Multimedia Description Schemes (DSs) for describing and annotating visual content. Qasim Iqbal and J. K. Aggarwal [7], they combined structure, color and texture for efficient image retrieval. Structure was extracted by the application of perceptual grouping principles. They stated that further research is needed to obtain a better performance in sub-classification. S. A. Chatzichristos and Y. S. Boutalis [8] proposed a composite feature descriptor that combined color and texture in a single quantized histogram. The proposed feature
This paper proposes a new approach that combines the global descriptor with a local descriptor which improves the overall result.

A color auto-correlogram

A histogram is a helpful tool in color image analysis. A histogram is a global statistical descriptor that represents the distribution of colors in an image. Histograms carry the statistical information of the three components of the used color space. A histogram-based retrieval system requires a suitable perceptually uniform color space such as RGB, HSV and YCbCr. The histograms color in image retrieval has both merits and weakness. Such merits are, robust, fast, Low storage requirements and straightforward to implement. In addition to the weakness are: there no spatial information of the color distribution and immune to lighting variations. In constructing such a histogram, the lake of the spatial distribution of colors can lead to erroneous similarity results between images. This paper overcomes this problem by integrating with texture feature. A color correlogram expresses how the spatial correlation of pairs of colors changes with distance (the term “correlogram” is adapted from spatial data analysis. A color histogram (henceforth histogram) captures only the color distribution in an image and does not include any spatial correlation information. The auto correlogram also readily discriminates distributions of points that display a tendency for clustering, or for anti-clustering (avoiding being positioned close to one another). The color histogram is one of the most important techniques in content-based image retrieval. It’s efficient to compute and effective in searching results. Most commercial CBIR systems use color histograms as one of the features. For an m*n image I, the colors in that image are quantized to C1, C2, ….., Ck. The color histogram H(I)={h1, h2, …., hk}.

The color histogram is easy to compute. It only needs to go through the image once, so the computation complexity is $O(n^2)$. And because color is one of the most prominent perceptual features, in many cases the effect of using histogram to searching and retrieving image is quit good. The weak point of the histogram method is there is no any space information in color histogram. There are several techniques proposed to integrate spatial information with color histograms. The “Color auto-correlogram” is one of these techniques. Consider the following question: pick any pixel $p_1$ of color $C_i$ in the image I, at distance $k_i$ away from $p_1$ pick another pixel $p_2$, what is the probability that $p_2$ is also of color $C_i$?

We define the auto-correlogram of image I for color $C_i$, with distance $k_i$:

$$\gamma_{c_i}^{(k)}(I) \equiv \Pr[| p_1 - p_2 | = k, p_2 \in I_{C_i} | p_1 \in I_{C_i}]$$

So the color auto-correlogram shows how the spatial autocorrelation of color changes with distance. The auto-correlogram integrates the color information and the space information. For each pixel in the image, the auto-correlogram method needs to go through all the neighbors of that pixel. So the computation complexity is $O(k \ast n^2)$, where $k_i$ is the number of neighbor pixels, which is depended on the distance selection. The computation complexity grows fast when the distance $k_i$ is large. But it’s also linear to the size of the image.

Similarity measure of A color auto-correlogram

The histogram intersection method is robust in respect to changes in image resolution, histogram size, occlusion, depth, and viewing point. The histogram intersection is used along with the histogram to measure the distance between images; this distance is used as the global score of the image. The histogram comparison methods provide a similarity measure for matching images based on their extracted histogram. The similarity ratio that belongs to the interval [0, 1] is compared to a given threshold. It can be described by:
where, $Q_H$ represents the query histogram, $H_C$ represents the histogram to be compared, and (i) represents the number of bins.

**geometric moment Descriptor**

Shape descriptions are an important task in content-based image retrieval. It is a mapping that converts the shape space into a vector space and satisfies the requirement that two similar shapes will also have close-to-identical shape descriptors [9]. Fourier descriptors (GD) prove to be more advantageous than other techniques in terms of computation complexity, robustness, easy normalization and retrieval performance [10]. The two-dimensional moment (for short 2-D moment) of a 2-D object $R$ is defined as:

$$m_{pq} = \iint_R x^p y^q f(x, y) dx dy$$

(2)

where $f(x, y)$ is the characteristic function describing the intensity of $R$, and $p+q$ is the order of the moment. In the discrete case, the double integral is often replaced by a double sum giving as a result:

$$m_{pq} = \sum_{R} x^p y^q f(x, y)$$

(3)

with $f(x, y)$, $p$ and $q$ defined in equation (1), where $(x, y) \in Z^2$.

The three-dimensional geometric moment (for short 3-D Moment) of order $p+q+r$ of a 3-D object is defined as:

$$m_{pqr} = \iiint_R x^p y^q z^r f(x, y, z) dx dy dz$$

(4)

**Similarity Measures of geometric moment**

The Bhattacharyya distance [11] is used along with the geometric moment to measure the distance between the query and the target shape feature vectors; this distance is used as the local score of the image.

The histogram comparison methods provide a similarity measure for matching images based on their extracted histogram. $Q_H$ represents the query histogram $H_C$ represents the histogram to be compared. This distance measured the statistical separability between spectral classes. It was a probabilistic distance measure that provided an estimate of the probability of correct classification. This distance overpasses zero histogram entries. This distance is given by:

$$B(H_Q, H_C) = -\ln \sum_i H_Q(i) \cdot H_C(i)$$

(5)

where, $Q_H$ represents the query histogram, $H_C$ represents the histogram to be compared, and (i) represents the number of bins.
Performance Evaluation

Precision and Recall are metrics to calculate the ranking of the images returned by the retrieval system [12]. For a query \( q \) having a defined ground truth images over a database \( R(q) \), and let \( Q(q) \) be the retrieved result of images for that query. The precision of the retrieval is defined as the fraction of the retrieved images that are indeed relevant to the query [13].

\[
\text{Precision} = \frac{|Q(q) \cap R(q)|}{|Q(q)|}
\]

(6)

The recall is the fraction of the relevant images that is returned by the query.

\[
\text{Recall} = \frac{|Q(q) \cap R(q)|}{|R(q)|}
\]

(7)

To evaluate a system over all the categories, Top N performance measurements [14] can be used. When submitting a query \( q \) to a CBIR system, the system returns \( N \) resulted list of images sorted based on similarity to the query image, where \( N \) is the number of top similar images. We denote \( PR_j \) as the precision of the top \( N \) returned sorted results. The aim of the user after submitting a query is to search for the most relevant images \( R(q) \). The precision

\[
PR_j = \sum_{i=1}^{N} \psi(p_i, R(q))
\]

(8)

So the average precision for all queries performed on a CBIR system for a certain \( N \) number of returned results is defined as:

\[
\bar{PR}_N = \frac{\sum_{i=1}^{\text{Total Query count}} PR_N(q_i)}{\text{Total Query count}}
\]

(9)

Similarly, the recall \( RE_j \) of the top \( N \) results of a query \( q \) is defined as:

\[
RE_N(q_i) = \sum_{i=1}^{N} \psi(p_k, R(q))
\]

(10)

And the average Recall for all queries is defined as:

\[
RE_N = \frac{\sum_{i=1}^{N} \psi(p_k, R(q))}{\|R(q)\|}
\]

(11)

The proposed Image Retrieval System

The proposed approach combines local description with global description. The A color auto-correlogram descriptor is applied globally on the whole image to capture the color information from all the pixels of the image. The Bhattacharyya distance is used along with the YCbCr A color auto-correlogram to measure the distance between images; this distance is used as the global score of the image. Another local score is defined by applying the local description technique to extract and texture information. The final score between two images is given by
\[ \Delta_{\text{finalScore}} = w_1 \times \Delta_{\text{Global Score}} + w_2 \times \Delta_{\text{local Score}} \]

Where \( w_1 \) and \( w_2 \) are the weights for global histogram and the edge histogram descriptor. This score increases with the increase of similarity to the query image. In our experiments, \( w_1 \) and \( w_2 \) are equal to one each; giving an equal importance to both global and local description of an image.

**RESULTS**

The experiments were executed on the 1000 image Wang database [15] and the Uncompressed Color Image Database (UCID) [16]. The Wang database includes 10 categories; each category contains 100 images. For each query a set of ground truth images that are relevant to the query were identified. Wang database have 20 queries each with a proposed ground truth. The UCID consists of 1338 uncompressed TIFF images of different topics related to indoors, outdoors and natural scenes, and man-made objects. UCID database have 162 queries each with a proposed ground truth. The results of the proposed approach have been compared with the results of the following MPEG7 descriptors: Scalable Color Descriptor (SCD), Color Layout Descriptor (CLD), and Texture Descriptor: Tamura Descriptor. Also the results have been compared to the fuzzy color and texture histogram (FCTH) composite descriptor.

The evaluation of the top N precision results for the proposed approach compared to other approaches over the Wang database is shown in figure (2). The evaluation of the top N recall results for the proposed approach compared to other approaches over the Wang database shown in figure (3). Figure (4) shows the experimental results of the mean precision for each category in the Wang database. Figure (5) shows the experimental results of the mean recall for each category in the Wang database. It is shown that proposed technique is better accurate than the previous approaches for categories.

Figure (6) shows the evaluation of the top N recall results and the top N precision evaluated over the UCID. Consistent with the results the proposed technique is better accurate than the previous approaches.

**CONCLUSION**

In this paper a new approach for image retrieval that integrates the proposed A color auto-correlogram and shape extraction technique. The new approach extracts the A color auto-correlogram as global statistical descriptor that represents the distribution of colors in an image. A histogram intersection used as similarity measure to detect the final image rank. The recommendation of the integration between global and local features has been explored by combining our approach with another local feature technique (GD). The experimental results showed that this combination provide more accurate results than MPEG7 color and texture descriptors and fuzzy color and texture histogram composite descriptor. The proposed approach is accurate in retrieving images even in the presence of geometric deformations or large occlusion and noise. This has the effect of improving the retrieval results and the extension of the proposed algorithm for semantics image retrieval.
Fig. 2. shows evaluation of the top N precision results for proposed approach compared to other approaches over Wang database.

Fig. 3. shows evaluation of the top N recall results for proposed approach compared to other approaches over Wang database.

Fig. 4. the mean precision for each category in the Wang database.
a. shows evaluation of the top N precision results for proposed approach compared to other approaches

b. shows evaluation of the top N recall results for proposed approach compared to other approaches

Fig. 5. The mean recall for each category in the Wang database

Fig. 6. The evaluation of the top N recall results and the top N precision over UCID database

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