Content-Based Image Retrieval through Combined Data of Color Moment and Texture

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Abstract
Feature extraction and presentation is of the most critical issues in content-based image retrieval (CBIR). CBIR system commonly extracts retrieval results respecting to the similarities of the extracted feature of the given image and the candidate images. In these systems, primary image features such as color, texture, shape and location are autonomously extracted and stored as a feature vector in a database for image comparison. This paper presents a new approach for content-based image retrieval based on color and texture data. In this regard, color histogram and color moment are used as color feature; further, PCA statistical method is applied to reduce dimensions.

Keywords:
Content-based image retrieval (CBIR), search and retrieval, texture extraction, color moment

1. Introduction

With internet popularity and development, multimedia data including videos and images have remarkably increased in our daily life. Accurate and rapid information retrieval among a massive collection of multimedia data is now turning into a hot research topic.
Content-based image retrieval is established as one of fundamental and interesting areas [1-4]. However, CBIR has been a highly active research area since 1990; there still remain some challenging problems due to complex image data. The problems stem from long-term challenges of most interdisciplinary research areas such as machine vision, image processing, image database and machine learning.
In a CBIR system, the image is retrieved based on image visual content including color, shape, texture and etc., which distinguishes conventional key term-based image retrieval (KBIR) systems [5].
KBIR retrieves the image through matching key terms as image, descriptions, tags, as well as annotations, etc. KBIR often rejects the irrelevant results due failure:

1. Key terms depend on the individual adding them; so, different people may attribute various meanings to an image.
2. Image annotation requires time and cost.

Nonetheless, CBIR primary studies only benefited one feature to describe an image, which is inadequate since the image is characterized with various visual features. Now, active works on image retrieval combine different visual features.
Color is of the widely used features that may be variously described including color histogram [6], color correlogram [7], color moment [8], color structure descriptor and scalable color descriptor [9]. Among these approaches, color moment is assigned the minimum dimensional vector and the least computational complexity; therefore, it is largely proper for image retrieval.
Texture is regarded as other widely sued features. Conventional methods of texture description may include gray co-occurrence matrix [10], Tamura texture feature [11] and Gabor filter feature. The present paper provides a new image retrieval method based on color features. How color feature and texture are extracted is elaborated in the following and the similarity criterion is stated; then, experiment results and comparisons are presented; and finally, it concludes.

2. Feature extraction

Feature extraction approaches are sub-divided into two classes of high-level and low-level feature extraction. Low-level methods refer to color and texture features; as mentioned, it provides an overall view of the image and its features. However, location parameter, to a large extent, may be involved in color and texture feature extraction by image zoning i.e. in zoning, it is determined that the features of an area of image are compared by features of the corresponding area.

2.1 Color histogram

Color is considered as image basic features that is more intuitive and obvious in image and is easily extracted. Many approaches are described by color, one of which is referred as color histogram [12]. Actual color is sampled by color statistical diagrams (histogram). Not only the color supplements to the subject beauty, but also it gives further information used as robust tools in image retrieval basic value.
The aim of a doubtful color indexing is to retrieve all the images sharing similarities in color combinations and

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texture to the considered color. There are several methods in image color retrieval.

Swine and Balard (1991) proposed the method of ‘indexing’ that represented used subjects in color indexing graph. Histograms are a way to express and display color development and spreading in images where each histogram box represents a color in a proper colorful context [13]. Histogram interval of the certain color and pictograph may be applied to depict and to match the similarity of two releases.

Mehtari et al (1995) suggested bicolor methods naming method interval and color method list source for image retrieval in order to overcome the difficulty of histograms.

In data extraction, the histogram is made by RGB component columns. Histogram embraces 48 columns where each defines a small scope of pixel values. The stored values per columns are image pixels within this range. These ranges show different levels of RGB components. The values, per columns, are obtained by distributing all pixels in images [14]. The problem with this approach is that images look completely different may have quite similar color histogram such that increased numbers of data base images may lead to higher failure. Vector approach was introduced to fix color histogram flaws. This method tried to apply additional restrictions reflecting pixel location on the conventional histogram. Existing pixels in histogram intervals are subdivided into two ‘integrated’ and ‘non-integrated’ categories in terms of local characteristics. An integrated pixel is a part of recognizable, continuous area; whereas, non-integrated pixel lacks such feature. The main fault of this approach is the slow extraction of image feature vectors.

2.2 Color moment

It is known as one of the most successful color extraction methods in retrieval systems. First-order, second and third moments as color mean, variance and bias, respectively [14, 15] effectively and optimally provide image color distribution. Image first to third moments are attained by (1-1)-(1-3):

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij} \qquad (1-1)$$

$$\delta_i = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij}-\mu_i)^2\right)^{1/2} \qquad (2-1)$$

$$\delta_i = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij}-\mu_i)^3\right)^{1/3} \qquad (3-1)$$

Where, f_{ij} is the ith color component and jth pixel; n is the number of image pixel. Color moments are often prioritized in HSV and L*a*b* systems. Using color third moment along the two first moments may increase retrieval overall efficiency; however, it is sensitive to any change in angel of view, which may lead to reduced efficiency.

2.3 Texture

Texture is another critical image feature and a uniform pattern in visual perspective obtained by the presence of more than one gray color. Texture extraction methods are categorized in to three classes [20]:

1. Structural methods
2. Statistical methods
3. Transforming methods
4. Model-based methods

Structural methods include morphologic operator and neighborhood graph defining the texture in terms of structural features, rules of pixel arrangement and so-called micro-textures. These approaches are proper for normal textures are mostly used for texture composition rather than texture analysis; despite, precise definition of the texture, they are not effectively efficient requiring huge computations. Today, structural approaches are only applied for particular purposes.

2.3.1 Texture extraction: neighborhood matrix

This matrix known as second-order histogram or gray-level co-occurrence matrix (GLCM) deals with cumulative probability distribution of pair pixels and is viewed as a highly successful method in texture definition. GLCM represents the presence frequency of both pixels in a certain interval of the image; the interval is regarded as vector or preset. Once the matrix is estimated, characteristics such as energy, entropy, contrast and homogeneity are extracted that may represent image existing texture. Ervis et al [21] introduced another texture extraction by this matrix.

2.3.2 Texture extraction: wavelet transform

One-dimensional discrete wavelet transform analyzes a discrete signal f(x) according to scale function values (X)φ and the shift and extended function ψ(X). (4-1) represents this transform in which $\varphi_{j0,l}$ and $\psi_{j0,l}$ are obtained by (5-1) and (6-1), respectively [22].

(x)ψ is called mother wavelet or in short, wavelet. Image wavelet (2D signal) is transformed through implementing one-dimension wavelet transform in vertical and horizontal directions.

$$f(x) = \sum_{l\in z} S_{j0,l}\varphi_{j0,l}(x) + \sum_{j\geq j_{0,l}}\sum C_{j,l}\psi_{j,l}(x) \qquad (4-1)$$

$$\varphi_{j,i}(x) = 2^{\frac{j0}{2}}\varphi(2^{j0}x-1) \qquad (5-1)$$

$$\psi_{j0,i}(x) = 2^{\frac{j}{2}}\psi(2^{j}x-1) \qquad (6-1)$$

3. Likelihood criterion

Similarity of two images is specified by the interval of the extracted features or by the distance between feature vectors. In other word, the two vectors' likelihood function portraits the feature in a positive real value by means of which the visual features are compared in both images. The criterion presenting human recognition-based image dissimilarity significantly decreases semantic distance and increases semantic-based retrieval achievement. To determine image dissimilarity, the interval of feature vectors is estimated. Multiple replies are obtained through using various criteria in specifying image dissimilarity. While, the two images share relatively close low-level features; they enjoy quite different semantic features.

3.1 Minkowski distance

Minkowski distance is clarified in term of L_p norm as follows [18]:

$$d_p(Q,T) = \left(\sum_{n=0}^{N-1} Qi - Ti)^p\right)^{\frac{1}{p}} \qquad (7-1)$$

Where, T= $\{T_1,\ldots, T_N\}$ and Q=$\{Q,\ldots,Q_N\}$ in which Q and T are indeed, inquiry and target image feature vectors.
For p=1 and d_1 (Q, T) is city block distance or Manhattan distance (L_1).

$$d_1(Q,T) = \sum_{i=0}^{N-1} |Qi - Ti| \qquad (8-1)$$

For p=2 and d_2 (Q, T) is L_2 Euclidean distance.

$$d_2(Q,T) = \left(\sum_{n=0}^{N-1} Qi - Ti)^2\right)^{\frac{1}{2}} \qquad (9-1)$$

For $p\to\infty$; then, we have L_∞:

$$L_\infty(Q,T) = \max_{0\le i\le 1}\{|Qi - Ti|\} \qquad (10-1)$$

4. Database

In a pilot implementation of a database, 1570 images were used. This database consists of 10 classes. All images of a semantic class share common semantic feature; though, they may vary in term of low-level features.

5. Evaluation method of image retrieval algorithm performance

The most common data retrieval evaluation criteria include precision and recall criteria. The two criteria are illustrated as a graph, known as PR, in which the precision is drawn respecting to recall [17].
Precision and recall rate is widely applied for retrieval performance measurement, which is mainly based on decisive match. In this approach, a data set is transformed into a binary set in term of relevance or irrelevance of the inquired image.
Retrieval results are examined by the known precision and recall criteria, which are defined as follows:

$$P_j = \frac{\text{number of retrieved and relevant elements in the first j position}}{j}$$

$$R_j = \frac{\text{number of retrieved and relevant elements in the first j position}}{\text{total number of relevant elements in the collection}}$$

According to the aforementioned formula, increasing j may descend Pj and ascend Rj. High initial value of Pj, close to one, gradually decreasing and rapid increasing of Rj value indicate algorithm high quality. This paper introduces the precision level of the proposed system and system [23].

6. Conclusion

According to the precision of the recommended system and system [23], it is seen that the proposed method outperforms the system in [23]; furthermore, the precision and recall diagrams of the proposed and [23] systems are illustrated in Figures 1 and 2, respectively

Table 1: Precision comparison of the proposed and [23] systems

Proposed method	[23] model	Input image
0.55	0.409	Africans
0.48	0.394	Beach
0.38	0.305	Building
0.60	0.737	Bus
0.93	0.588	Dinosaur
0.52	0.491	Elephant
0.77	0.711	Flower
0.83	0.525	Horse
0.48	0.630	Mountain
0.70	0.312	Food

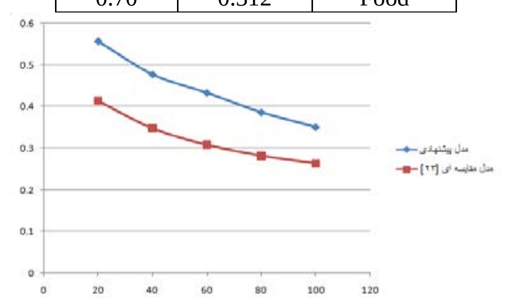

Figure 1: Precision diagram

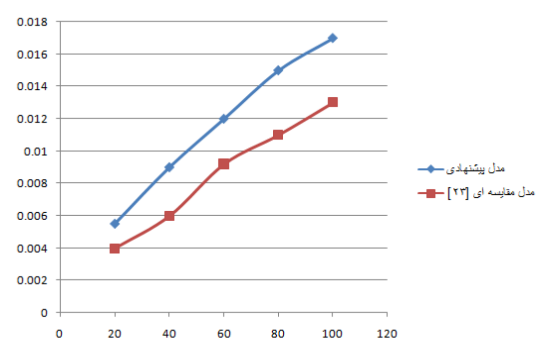

Figure 2: Recall diagram

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