Applying Association Rules to Designing an Efficient Image Retrieval Model

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Abstract

Content-based image retrieval systems serve people to seek for relevant and desired images in a more efficient way. What kind of embedded features to be extracted from the images remains the primary concern and the users' perception is ignored in the conventional models. An association rule based image retrieval model is proposed in this paper. We focus on the users' intentions while retrieving the interesting images. To provide a more efficient retrieval model, four main tasks have been accomplished: low level feature extraction, image segmentation and representation based on a fuzzy gray level inference model, image searching engine and users' behavior mining engine. Experimental results verify that by exploiting the association rules in the image retrieval model can narrow down the searching space and return the desired images faster than the conventional methods.

Keywords: content-based image retrieval, data mining, fuzzy segmentation.

1. Introduction

As we march into the digital age, the data overload problem is ahead of us. The digital information with its convenient sharing and distributing properties has grown rapidly in volume and size. This trend drives the needs of developing efficient methods to retrieve the contents of such data. The modern multimedia technologies have led to a vigorous development of practical issues in retrieving media data. One is the image retrieval system. The conventional image retrieval systems, which search the relevant images by captions manually attached to the images, consume considerable time and labor. Due to limited number of alphanumeric letters, most users will have different semantic concepts to describe the same object. Meanwhile, this keyword approach does not utilize the image contents while retrieving images. Moreover, it does not take the human intuition and emotion into account in retrieving images. The searching results always cannot comply with the users' initial expectation. The content-based image retrieval (CBIR) systems were proposed in the early 1990 to overcome the obstacles of text or keyword-based approach.

The CBIR systems consider human visual effects by analyzing low-level content features such as texture [1], color [2], shape [3], and location properties. Based on specific features derived from images, users can find the most similar images from the database. Rui et al. [4] used a geometric distance-based similarity method to compute the overall image similarity. Meihac and Nastar [5] relied on a probabilistic likelihood-based measurement to denote the similarity of images. Vries et al. [6] utilized the BOND algorithm to reduce the similarity computation in retrieving the k-nearest neighbors from an image database. However, the features extracted from image raw data are not sufficient to describe the high-level semantics. There exists a gap between the low-level features and high-level semantics. As a result, it causes a serious obstacle that two different semantic objects may share the similar low-level features, while two similar objects may stay far away in feature space.

To bridge the gap, some researchers proposed two approaches: the region-based approach to capture the users' focus [7] and the relevance feedback mechanism to intensify the users' interests. In this paper, we propose a fuzzy region-based image retrieval system incorporating association rules to analyzing users' retrieving intentions. The organization of this paper is as follows. Section 2 describes the overview system architecture. Section 3 proposes the image retrieval method. In section 4, we describe the retrieval methodology. Section 5 introduces the relevance feedback coupled with data mining. We complete the paper with some conclusions and future research issues in section 6.

2. System Overview

We implement our system in Visual C++ 6.0 and Borland C++ Builder 6.0. There are 1,000 general purpose color images in the database. In our system, we classify our system into four tasks as follows. First, we segment each image into several regions in the preprocessing phase. The system provides a user query interface in the region-based retrieval portion. The retrieval mechanism is described in user query phase. Finally, the image data mining algorithm can analyze users' intentions in retrieving images.

3. Fuzzy Image Segmentation

The human vision and perception of recognizing images will show some degrees of uncertainty especially for similar colors. The fuzzy set theory can help quantify the uncertain color space.

1. Fuzzification: A fuzzifier performs the fuzzification function and converts a crisp value into a fuzzy set by using a membership function. For example, a specific value x_i belongs to a fuzzy set $T^1_{X_i}$ with a degree $\mu^1(x_i)$ and to a fuzzy set $T^2_{X_i}$ with a degree $\mu^2(x_i)$, and so on. As the fuzzy set T^i, the different levels of luminance are defined by the luminance membership function. Similarly, different membership functions can be defined for hue and saturation.

2. Fuzzy Reasoning: Fuzzy modeling characterizes the relationship between input and output of a system by some fuzzy rules. The fuzzy rules are conditional statements like the form of *IF-THEN* as follows.

R^1: If luminance is black and hue is violet and saturation is low, then fuzzy gray level is low.

R^2: If luminance is black and hue is violet and saturation is medium, then fuzzy gray level is low.

…

R^{54}: If luminance is white and hue is red and saturation is high, then fuzzy gray level is high.

3. Defuzzifier: The defuzzifier performs the defuzzification function, which maps a fuzzy space into a crisp output. It derives a crisp output by approximate reasoning that best represents the possibility distribution of an inferred control action. To derive the output, the center of area (COA) is used:

$$Z^*_{COA} = \frac{\sum_{i=1}^{r} \mu_C(z_i) z_i}{\sum_{i=1}^{r} \mu_C(z_i)}. \quad (1)$$

The COA generates the center of gravity of the possibility distribution of a control action. By considering all the effective components of HLS, a pixel can have the fuzzy gray level after previous steps.

4. Labeling: After mapping the RGB components of a pixel to the fuzzy gray level, we can continue the image segmentation. The image segmentation procedure starts with a single pixel as the first region. Then the system examines fuzzy gray level f_i of each pixel and decides its proper inclusion to a cluster. The model repeats the clustering process until all pixels of an image are properly classified into different classes. During the processing procedure, we have to calculate each cluster center. Fuzzy c-means method repeats the Euclidean distances to decide the cluster centers. After the processing, we can classify pixels into different classes. The system defines c clusters such that the partition set can be denoted by $A = \{A_1, A_2, ..., A_c\}$. The fuzzy pseudo partition set A must satisfy the following conditions.

$$\sum_{j=1}^{c} A_j(x_i) = 1, \text{ for all } i \in N_n. \quad (2)$$

$$0 < \sum_{j=1}^{c} A_j(x_i) < n \text{ for all } i \in N_c. \quad (3)$$

The fuzzy clustering can find the partitions and the associated clusters by which the structure of the data is represented as best as possible. After all the pixels are classified, the association will be strong within clusters and weak between clusters. And the set of cluster center vector $V = \{v_1, v_2, ..., v_c\}$ associated with each image in database can be calculated as follows.

$$v_i = \frac{\sum_{k=1}^{n} [A_j(x_k)]^g x_k}{\sum_{k=1}^{n} [A_j(x_k)]^g}, \quad (4)$$

where g is a real number and $g > 1$. Each region consists of m pixels and can be represented as follows.

$$\text{Region} \quad R = \bigcup_{i=1}^{m} P_i. \quad (5)$$

The image segmentation partitions an image into r disjoint regions denoted as $R_i, i = 1,2,...,r$. An image I is the union of all segmented regions:

$$\text{Image} \quad I = \bigcup_{i=1}^{r} Ri, \quad Ri \cap Rj = \Phi \quad for\ i \neq j. \quad (6)$$

4. Image Retrieval

Following, we calculate the histograms of each region to form color feature vectors, which represent pixel color statistically over an image. We compute the region similarity according to the color histogram.

In the user query stage, we will provide some sample images, which have been segmented into some regions. The system will execute similarity measurement after the users submit their queries. Then our system would pop-up the top 5 most similar images. The users can continue the search until they are satisfied with the searching results.

In the query processing stage, the regions of each sample image are displayed using different colors to aid users' selection. The users can select some regions that they are interested in and then feed back to the system. At the same time, they can set up the weights to adjust the importance of the chosen regions. After the selection and feedback, an overall similarity measurement will be ranked to direct the database search for target images.

We log all the users' selections each round while they retrieved interesting images. After the users complete the retrieval, the system will boot the mining processes. We store the association rules derived from the mining procedures in database. When next user executes the retrieving, the system will recommend the matched images according to selected regions and association rules. While the logged data increases, the system can infer users' intentions more in agreement.

5. Image Data Mining Model

The well-known relevance feedback technique can bridge the gap between low-level features and semantic meanings. This strategy alters the weights of user's current queries and previous retrieved information. The main drawback of this approach is in considering only current query session but forgetting the users' past interactions. In fact, the relevance feedback can reflect the users' intentions in searching for desired images. Data mining can find out the correlations between merchandises from a transaction database. This technique can conduct the association rules to infer interesting regularities in a data set. Association rules have been used in applications such as super market analysis to capture relationship among items in large data sets.

In our system, while users retrieve the desired images, they can select interesting regions and set the relevance weight w_i for a region R_i. The system will map the weight to the linguistic variable based on the membership functions. This selection will be logged as (R_i, var). The R_i represents a query region and *var* belongs to a linguistic label set. Currently, we define three linguistic labels to represent user's interest of a region. For example, when one user sets w_i as 60 for a region R_i, the system will infer the membership degrees of that region to 0.8 and 0.1 for linguistic MR and linguistic HR, respectively. We will record the selection in the form of (R_i, MR). The idea is to treat the selected regions as purchased items and to store all transactions in database.

After the users finish retrieving images, our system begins to infer the association rules. We define the sequential patterns mining as follows. Let $I = \{i_1, i_2, ..., i_m\}$ be a set of m distinct attributes (so called items). An itemset is a non-empty collection of unordered items. A sequence is an ordered list of items. An itemset S is denoted as $(i_1, i_2, ..., i_k)$, where i_j is an item belonging to I $(i_j \in I)$. An itemset with g items is called a g-itemset. A sequence α is denoted as $(\alpha_1 \to \alpha_2 \to ..., \to \alpha_q)$, where the sequence element α_j is an itemset. A sequence with k items $(k = \sum_j |\alpha_j|)$ is a k-sequence. For example, $(A \to BC)$ is a 3-sequence. An item can occur only once in an itemset, but it also can occur in other itemsets of a sequence. A sequence $\alpha = (\alpha_1 \to \alpha_2 \to ..., \to \alpha_n)$ is a subsequence of another sequence $\beta = (\beta_1 \to \beta_2 \to ..., \to \beta_p)$ and will be denoted as $\alpha \prec \beta$, if the existence of $i_1 < i_2 < ... < i_n$ will implicate $\alpha_i \subseteq \beta_j$ for all α_i. For example, the sequence $(A \to BC)$ is a subsequence of $(AB \to E \to BCD)$ because of $A \subseteq AB$ and $BC \subseteq BCD$. On the other hand, the sequence $(AB \to D)$ is not a subsequence of (*ABD*). According to the above definitions, we can construct sequences by using Apriori algorithm.

For illustration, assuming the system has eight regions (A to H), 4 users, and 10 transactions. One user's selection is logged as shown in Table 1. We are only interested in high preference region from users' selection. Hence, the system chooses the region with HR label and ignores some uninterested regions as shown in Table 2. We construct all the frequent sequences with a minimum support of 50% or 2 transactions. As a result, we can infer a maximal frequent sequence $(D \to BF \to A)$ from this example as given in Table 3.

For the purpose of conveniently recording users' selections and mining users' intentions, we transform regions derived from color images into unique digits. After the transformation, the system can tell the subordinate relationships between regions and images by identifying the indexes. Whenever the users retrieve their desired images, the system will log the individual retrieval information of the region indexes and target image. In the post-processing phase, our system will mine the association rules. We store the rules in the rule base. For example, an inferred rule as "4, 6, 7, (452)", represents when a user selects region indexes of 4, 6, and 7, the system will immediately pop the homologous image 452. If the users are not satisfied with the mined images, they can continue the retrieval by content-based retrieval method until they find the most similar images. To verify the proposed region-based image retrieval model is closer to human visual perception, we present the search results in Fig. 2.

6. Conclusions

We proposed a region-based image retrieval model and incorporated data mining to improve the precision in retrieving images in this paper. Our model makes three main contributions to a region-based CBIR system. (1) A novel fuzzy region segmentation method is employed into the system. (2) This system takes the user's intuition into consideration and a user-oriented interface is designed to search the database directly. (3) Association rules can collaborate to achieve improving the retrieval precision. By integrating the image contents and association rules from the users' logs into the image retrieval model, the experimental results verify that the proposed model can narrow down the searching space and reply the desired images faster than the conventional methods.

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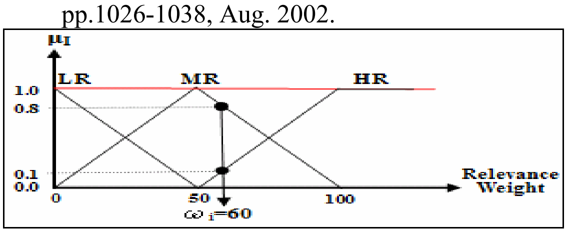

Fig. 1. Relevance membership functions.

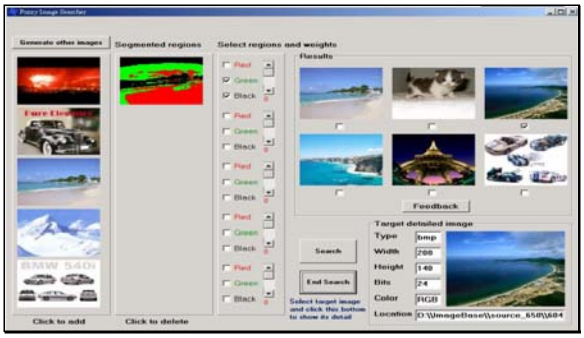

Fig. 2. The search for scenery images, target image 452.

Table 1: An example of one user's chosen regions.

User 1 Selected Region and Fuzzy Relevance with Region	Retrieving Round	Selected Regions and Fuzzy Relevance
	(1)	(R_A,MR),(R_C,HR),(R_D,HR)
	(2)	(R_A,HR),(R_B,HR),(R_C,HR),(R_G,LR)
	(3)	(R_A,HR),(R_B,HR),(R_C,LR),(R_F,HR)
	(4)	(R_A,HR),(R_C,HR),(R_D,HR),(R_F,HR)

Table 2: The logged transactions in database.

Database					
Trans. ID	**Retrieving Round**	**Items**	**Trans. ID**	**Retrieving Round**	**Items**
1	**1**	**C D**	**3**	**1**	**A B F**
1	**2**	**A B C**			
1	**3**	**A B F**	**4**	**1**	**D G H**
1	**4**	**A C D F**	**4**	**2**	**B F**
			4	**3**	**A G H**
2	**1**	**A B F**			
2	**2**	**E**			

Table 3: The frequent sequences.

Frequent 1-Sequences		Frequent 3-Sequences	
A	4	ABF	3
B	4	BF → A	2
D	2	D → BF	2
F	4	D → B → A	2
		D → F → A	2
Frequent 2-Sequences			
AB	3	**Frequent 4-Sequences**	
AF	3	D → BF → A	2
B → A	2		
BF	4		
D → A	2		
D → B	2		
D → F	2		
F → A	2		