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A New Framework of CBIR Based on KDD*

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Abstract: The researching emphases of CBIR (Content-based Image Retrieval) was put on the low-level visual feature extraction to resolve the problem of manual annotation for images in recent years. But because of variety of images, the extracted visual features can not express the semantic content of each image correctly. So the retrieval accuracy is lower than the text-based image retrieval accuracy generally. In this paper we propose a new retrieval method based on KDD (Knowledge Discover in Database) and knowledge reasoning to improve the retrieval accuracy and relate the low-level image features with the high-level semantic content. Experiment shows that the result is much better than the traditional retrieval method.

Keywords: Content-based image retrieval, KDD, Rough set, knowledge reasoning

1. Introduction

With the rapid growth of the digital information, the efficient browsing, searching and retrieval system for the useful information is always the increasing requirement to a user. In general, CBIR(Content-based Image Retrieval) is the set of techniques for retrieving semantically-relevant images from an image database based on automatically-derived image features. A number of general-purpose image search engines have been developed up to now, such as MIT Photobook[1], Columbia VisualSEEK and WebSEEK[2], and Stanford SIMPLIcity[3].

Compared with the previous text-based image retrieval, current Content-based Image Retrieval systems work mainly on low-level visual features of images to index the images by their own visual content, such as color, texture, shape and color layout. But extracted features are often context-dependent, and noisy, also their relevance for a query is dependent on the data and the task. And because of the variety of images, images having similar low-level visual features may be semantically very different. On the contrary, to large of images having same semantic content, their extracted low-level features are very different because of the diverse appearance of object. We argue that the features are incomplete and imprecise in expressing the semantic content of images compared with the perception of human. So it is very important to co-relate the low-level image features with the high-level semantic content, and retrieve images based on the semantic content.

Instead of requiring universal similarity measures , based on KDD (Knowledge Discovery in Database) and knowledge reasoning, a basic and preliminary CBIR system is developed utilizing extracted low-level visual features, along with the underlying semantic content input by the builder of system, for generating rules according a rule generation strategy in this paper. The rule generation strategy and classification mechanism are designed on rough set theory. Images are classified according to the generated rules and then further retrieved.

2. KDD and Rough Set[4]

In the database for image retrieval, besides the image data, there is a automatically extracted low-level visual feature comprising the record of every image. Our goal is to connect the visual feature with the semantic definition input at the time of constructing the CBIR system and get the classification knowledge used in retrieval based on semantic class from the database. That is a KDD process. In this paper, the goal is achieved concretely by rough set theory.

Rough set was introduced by Pawlak[5] in the early 1980s as a effective knowledge reasoning tool for imprecise, uncertain and incomplete information in data mining and KDD. The main idea of rough sets is to infer the decision or classification rules of problems by means of knowledge reduction assuming that the

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classification ability of information system keeps stable.

2.1 Information System

Information System (*IS*) is an ordered pair

$$\Lambda = (U; A) \tag{1}$$

where U is a nonempty finite set of objects, the *Universe*, and A is a nonempty, finite set of elements called attributes. The elements of the Universe are referred to as *objects*. A **decision system** is an *IS*, for which the attributes in A are further classified into disjoint sets of condition attributes C and decision attributes D.

2.2 Knowledge Reduction and Rule Generation

Knowledge reduction is to delete the irrelevant or unimportant knowledge (attribute) with the precondition of constant classification ability of knowledge database.

Dispensability: An attribute a is said to be dispensable in $B \in A$, if $IND(B) = IND(B-(a))$, otherwise the attribute is indispensable in B, where $IND(B)$ is called an Indiscernibility Relation, defined as follows:

$$IND(B) = \{(x,y) \in U^2 \mid a(x) = a(y) \;\; \forall a \in B\} \tag{2}$$

Reduct: A Reduct of B is a set of attributes $B_1 \in B$ such that all attributes $a \in B - B_1$ are dispensable, and $IND(B_1) = IND(B)$. The set of prime implicants of the discernibility function $f(B)$ determines the reducts of B. $f(B)$ is defined as:

$$f(B) = \underset{i,j \in 1,\ldots,n}{\wedge} \vee \overline{m_D}(E_i, E_j) \tag{3}$$

where $n = |U / IND(B)|$ and The entry $m_D(i;j)$ in the discernibility matrix is the set of attributes from B that discern object classes $E_i; E_j$ in $U / IND(B)$.

3. Rough Set Framework of CBIR and Implementation

Images are represented by low-level visual feature vectors in traditional CBIR. Define *vector space* V and feature vectors of images with m number, $\alpha_1, \alpha_2, \ldots, \alpha_m \in V$. Every vector is defined to be the n-tuple $(a_1, a_2, \ldots, a_n)$. The two-dimension table of image database is represented by the upper table in Fig.1. For example, a_{1n} is the n-th *component* of vector α_1.

We input the semantic content of the images into the table of database that changes into a decision system represented by the lower table in Fig.1 which also illustrates the process.

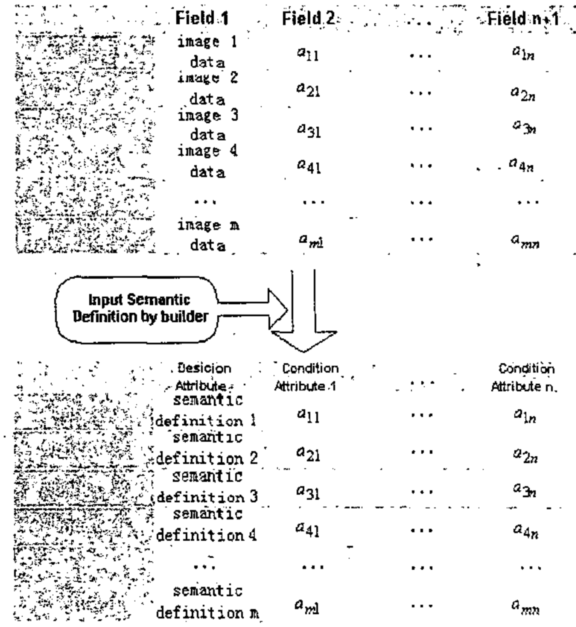

Fig.1. Transforming process from image database table to decision system

Based on the rough set theory, the dispensable attributes are reduced and classifying rules are generated in decision system. Thus we relate the visual feature with the high-level semantic content of images. The framework of CBIR based on rough set is illustrated in Fig. 2.

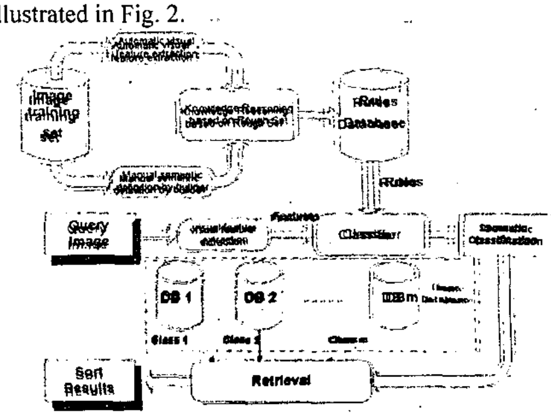

Fig.2. Framework of CBIR based on Rough Set

The following is the detailed methods of implementation:

3.1 Low-level visual feature extraction

Color feature is one of the most widely used visual features in Image Retrieval. It is relatively robust to background complication and independent of image size and orientation. The idea of using color moment for color indexing is simple. In this paper we extracted global color moments in HSV color space.

3.2 Discretization of feature vector

The feature vector obtained often contains components whose dynamic ranges can be very different. The feature vectors have to be scaled to integer values. In this paper, we use the equal frequency scaler to implement equal frequency binning.

3.3 Reduction and rule generation

The reducing algorithm[6] which we used is a simple greedy algorithm which has a natural bias towards finding a single prime implicant of minimal length. After the reduction, by binding the condition attribute values of the object class to the corresponding attributes of the reduct, adding the decision part, namely the semantic definition of images, which comprises the resulting part of the rule, and reducing the redundant rules, the rules base is generated.

3.4 Classification and Retrieval

In this paper, we use a voting mechanism in choosing the decision value to solve the problem of conflicting rules and more than one matching rule.

Every matched rule contributes votes to its decision value, which are equal to the number of objects supporting the rule in training set. The votes are added and the decision with the largest number of votes is chosen as the correct class. The entire image database is constructed by n separate databases with different semantic classes. Images chose partly from each database form the image training set. In image retrieval, the query image with extracted low-level feature is first classified according to the generated rules base. Then the similarity matching based on visual feature is done in the class which the query image belongs to.

4. Experimental Results

We choose 600 pictures from standard COREL photograph data set as our experimental image database. The images in the image database are grouped in 6 classes (100 images in a class). Under the same condition of extracting the global color feature of images, we compared our retrieval method with the method of global similarity measurement based on Euclidean distance. We show two rows of images with the top 11 matches to each query. The query image is the image at the upper-left corner of each block of images. For each query example, we manually examine the precision of the query result. Here we determine the semantic relevance of images according to the common judgements.

It can be seen that only the result of roses and sailingboat based on traditional method is good. The other retrieval precision of query results, especially tiger class, is very low. That shows that the background of images puts great influence on the query results. For our method, the examples in Fig.3 shows that the query images have been classified into correct classed by matching the rules. So query results are much better and our method achieves higher retrieval precision.

5. Conclusions and Future Work

In this paper, we have demonstrated a novel framework of CBIR. By knowledge reasoning based on rough set, the framework co-relates the low-level image features with the high-level semantic content, and retrieves images based on the semantic content. It does better classification than the conventional approach in our experiment when image database are finite and fixed. To solve the increasing of rules base when image database becomes larger, in the future work, the framework could be improved by using good rule pruning and retrieval strategy while decreasing the training set.

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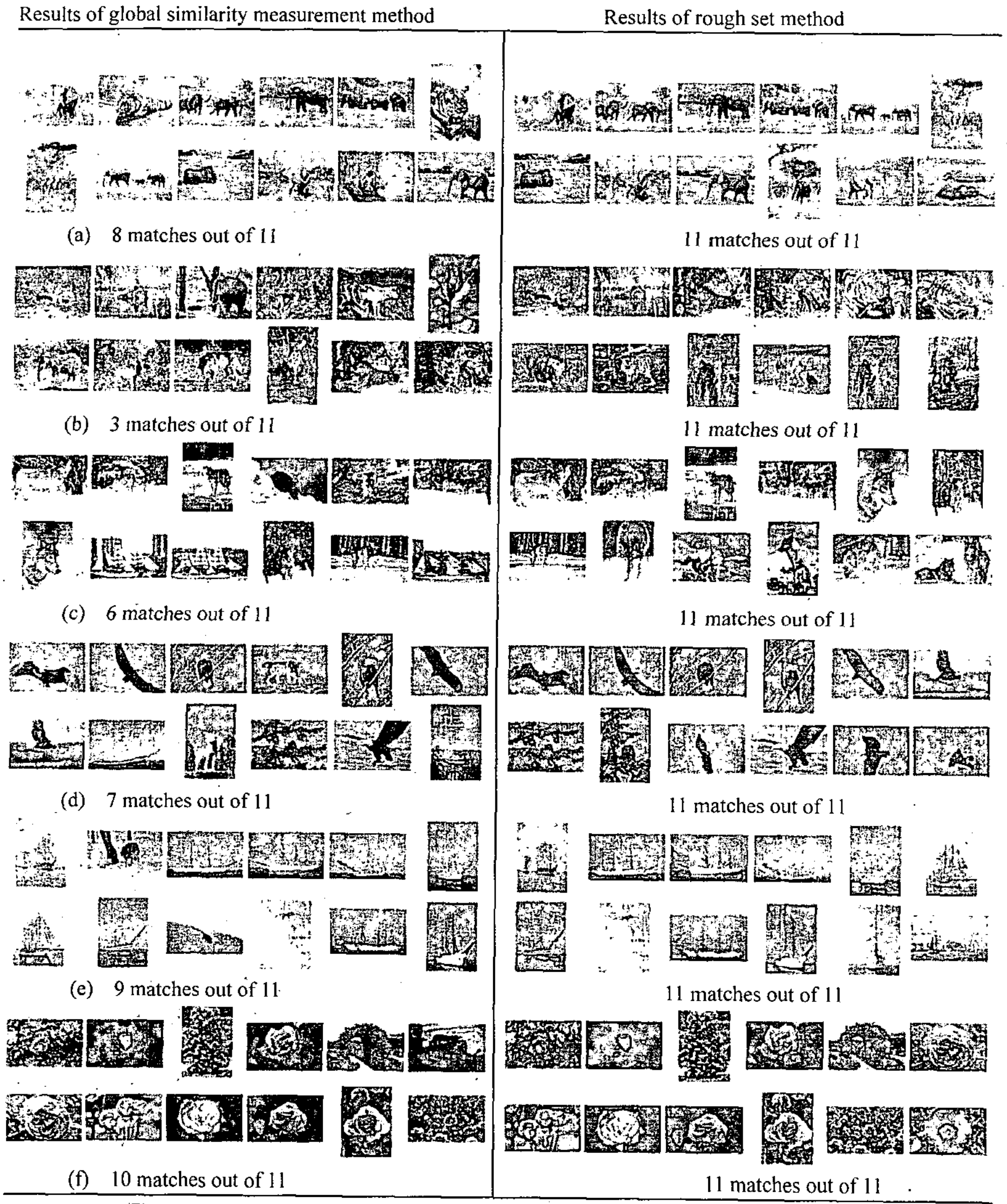

Fig. 3. Query results comparison of traditional method and rough set method. (a) elephant, (b) tiger, (c) wolf, (d) eagle, (e) sailingboat, and (f) roses.