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Relevance Feedback for Image Retrieval

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***Abstract*— In recent years the relevance feedback technology is regarded in content based image retrieval. The idea is to adopt the system to the specific user preferences making more important weights or features that reflect the actual user need in order to achieve higher precision. Therefore we can define relevance feedback as the process by which human and computer interact in order to automatically adjust the query to the real user preferences. The idea is to adjust the query selection criteria to better approximate real user need using the result retrieved by the original query. To be more profitable, relevance feedback techniques were incorporated into CBIR such that more precise result can be obtained by taking users feedback into account.**

***Keywords*— Relevance feedback, CBIR, Feature Extraction.**

I. INTRODUCTION

Relevance feedback [1] is a method to enhance the system search effect. It studies from the real interactive process of the user and the search system, then discovers and captures user's actual search intention, and modifies the search strategy of system, Image retrieval based on relevance feedback is an unceasingly repeated and gradually advanced processes. The interaction between the system and the user enables the retrieval to approach the user's expectation, and finally achieves the requests.

Image Retrieval is becoming a domain of increasing and crucial importance in the new information based society, as a part of Information Retrieval (IR) field. Image retrieval has been addressed in various ways [1], [2], [3], [4], [5], since with the increase of Internet bandwidth and CPU speed the use of images in the World Wide Web has become prevalent.

Information sharing has increasingly become a common phenomenon among the users of today's high speed network. Due to advancements in the digital photography technology, large storage capacity and high speed networks, storing large amount of images has become possible. Digital images find a wide range of application in the medicine, science, military and security purposes etc. Therefore there is a need for an efficient way for image retrieval. There are different ways to retrieve the images in CBIR. A big challenge in CBIR is the semantic gap between the low level feature and the high level concept. In order to reduce the gap between the low level feature and high level concepts, relevance feedback was introduced into CBIR [5], [6]. Recently, many researchers began to consider the RF is a classification or learning problem. That user provides positive and/or negative examples, and the system learns from such examples to separate all data into relevant and irrelevant groups.

II. ARCHITECTURE

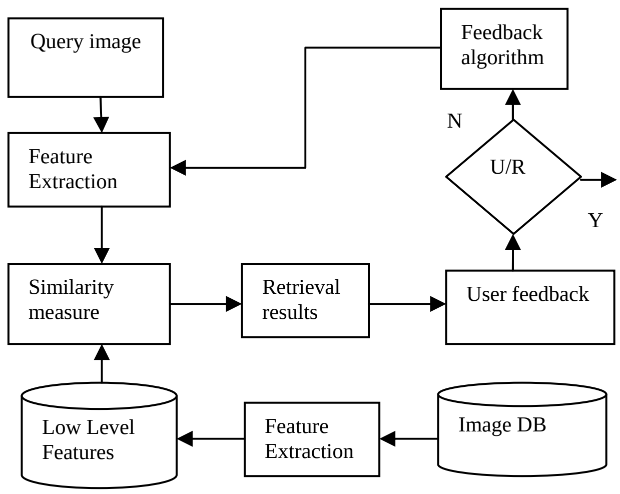

Fig. 1 A general description of standard image retrieval.

Fig.1. shows a general description of standard image retrieval from database using relevance feedback. These features can be classified as global features and local features. The most commonly used features are color, texture, and shape. They are all application independent. The basic idea of relevance feedback is to shift the burden of finding the right query formulation from the user to the system. In order to make this true, the user has to provide system with some information, so that system can perform well in answering the original query. To retrieve the image from the database, we first extract feature vectors from images (the features can be shape, color, texture etc), then store feature vectors into another database for future use. When given query image, we similarly extract its feature vectors, and match those features with database image features. If the distance between two images feature vectors is small enough; we consider the corresponding image in the database similar to the query. When searching more generic image databases, one way of identifying what the user is looking for in the current retrieval session (the target of the user) is by including the user in the retrieval loop. For this, the session is divided into several consecutive rounds; at every round the user provides feedback regarding the retrieval results, e.g. by qualifying images returned as either \relevant" or \irrelevant" (relevance feedback or RF in the following); from this feedback, the engine learns the visual features of the images and returns improved results to the user. The RF mechanism implemented in a search

engine should attempt to minimize the amount of interaction between the user and the engine required for reaching good results.

In fact, RF was first introduced for the retrieval of text documents in [7] .The ease with which the relevance of an image can be evaluated and the persistent difficulty of dealing with the semantic gap in CBIR explains the rapid development of RF for image retrieval since the early work in [8], [9], [10].

III. OBJECTIVE OF THE PROBLEM

The first and most frequent objective consists in finding images that share some specific characteristic the user has in mind. The case of target search studied in [11] and [12], where the user is looking for that particular single image she has in mind, was further distinguished from the more common category search.

A complementary but less frequent use of RF was introduced in [13] and consists in defining a class of images and extending textual annotations of some images in the class to the others. In the explore and search for some "relevant" items, the user has a rather vague prior notation of relevance and relies on the exploration of the image based to classify it. In the retrieve most items in the set of "relevant" one, the user would like to find all or most of the image that share some specific characteristic she has in mind.

IV. IMAGE REPRESENTATION

The representation of individual images also has an impact on the RF mechanism employed. In existing work on the CBIR with RF, two different representation schemes were used for the images:

- Most of the time, the global visual appearance of the images is described using a combination of global signatures including color, texture and shape information. Images are then represented by fixed-length vectors in a description space.
- In some publications, such as [14], [15] an image is considered to be a set of regions obtained by an automatic segmentation. Every region can be described by color, texture and shape. Additionally, some information regarding the configuration of regions can be available. An image is then represented as variable length collection of region signatures, possibly including configuration information. From user feedback concerning entire images, the search engine is also expected to learn which regions are important for the current search session and which regions to ignore.

V. GENERAL ASSUMPTIONS

One can customize an RF mechanism if one knows the characteristics of the scenario, of the target application and of its users.

1. The discrimination between "relevant" and "irrelevant" images must be possible with the available image descriptors.
2. There is some relatively simple relation between the topology of the description space and the characteristic shared by the images the user is searching for.
3. "Relevant" images are a small part of the entire image database.
4. While part of the early work on RF assumed that the user could (and would be willing to) provide a rather rich feedback, including \relevance notes" for many images, the current assumption is that this feedback information is scarce: the user will only mark a few \relevant" images as positive and some very different images as negative.

VI. RELEVANCE FEEDBACK MECHANISMS

The RF mechanism implemented in a search engine must operate in real time. It is expected to maximize the ratio between the quality of the retrieval results and the amount of interaction between the user and the system.

An RF mechanism has two components: a learner and a selector. At every feedback round, the user marks (part of) the images returned by the search engine as "relevant" or "irrelevant". The learner exploits this information to re-estimate the target of the user. With the current estimation of the target, the selector chooses other images that are displayed by the interface of the search engine; the user is asked to provide feedback on these images during the next round. The task of the learner is particularly difficult in the context of RF for several reasons. The amount of training data is very low, usually much lower than the number of dimensions of the description space. There are usually much fewer positive examples than negative examples recent work on RF often relies on support vector machines.

In RF, SVMs appear to be the learners of choice for several reasons:

1. The decision function of an SVM allows both the definition of a frontier and the ranking of images.
2. SVMs are very flexible.
3. SVMs are usually less sensitive than density-based learners to the imbalance between positive and negative examples in the training data.
4. SVMs allow fast learning for medium-sized databases.

While most of the existing work using SVMs for RF concentrates on 2-class SVMs[16], [17] that must learn to discriminate positive and negative examples, 1-class SVMs were also put forward in [18] in order to learn from positive examples only. 1 class SVMs are able to estimate the support of the distribution of positive examples.

A. Idea of Relevance Feedback

The relevance feedback mechanism had been introduced into the image retrieval system. The relevance feedback technology adjusts the search automatically according to the user's relevant feedback of the preceding retrieval result. The basic steps of user's relevance feedback are as follows

1. System search for the query image given by user.
2. The user compares the retrieval result returned from the system with own demands.
3. System analyses the character which can indicate user's retrieval aim best automatically from the feedback information produced by the user, adjusts the similarity method, then carries on the retrieval again, repeats the step 2.

Relevance feedback technology is the main domain in current image retrieval research. The aim of relevance feedback is to study from the real interaction between the user and the retrieval system. It discovers and captures user's actual search intention, and modifies the search strategy of system, thus obtains the search result which tallies as precise as possible with the user's actual demand.

B. Image Retrieval Mode of Relevance Feedback l Stage

To extract the characteristic needed in the content-based image retrieval, we consider the relevant problem and the user relevance feedback problem therefore must use a set of reasonable retrieval models to carry on to it, and then make the retrieval results may rely on. We explain the image retrieval model based on relevance feedback as follows.
First, we should define the object image models; an object image model I may be represented as:

$$I = I(D, F, R) \tag{1}$$

D is the raw image data, e.g. the image in JPEG form, etc. $F = \{f_i\}$ is the low level feature associated with image object.
$R = \{r_j\}$ is the expression of a certain characteristic f_i, the color histogram and the color matrix are the expression way of color characteristic, each characteristic expression r_j is possibly a vector which is composed by many components, can be written in the following form:

$$r_j = \{r_{j1}, r_{j2}, r_{j3}......r_{jk}\} \tag{2}$$

where k is the length of the vector.
The object model supports multiple representations with dynamically updated weights to accommodate the content in the image object. The image characteristic weight value exists in each level of the model, W_i , W_{ij} and W_{ijk} corresponds to the image characteristic f_i, the expression r_j, and the components r_{jk}. The aim of relevance feedback is to search for proper weight value.
Based on Relevance Feedback retrieval process is as follows:
1. Initialize the weight values $W = [W_i, W_j, W_{jk}]$ into WO, which is a set of no bias weights. That is every entity is initially of the same importance.

$$W_i = WO_i = \frac{1}{I} \tag{3}$$

$$W_j = WO_{ij} = \frac{1}{J_i} \tag{4}$$

$$W_{jk} = W_{ijk} = \frac{1}{K_{ij}} \tag{5}$$

Where I is the number of image characteristic, J_i is the number of representation for feature f_i , K_{ij} is the dimension of vector r_j.
2. Divide the query object Q provided by the user into group of image characteristics f_i according to the weight W_i.
3. Within each characteristic f_i can be divided into the corresponding expression r_{ij} according to the weight W_{ij}.
4. In certain characteristics expression r_j, the similarity between the image I and the query image Q is calculated according to the corresponding similarity algorithm m_{ij} and the weight value W_{ijk}:

$$S(r_{ij}) = m_{ij}(r_{ij}, w_{ijk}) \tag{6}$$

5. Each representation similarity value are then merge into feature similarity value:

$$S(f_i) = \sum w_{ij} S(r_{ij}) \tag{7}$$

6. The total similarity S between the image I and the query image Q can be obtained by combining individual $S(f_i)$:

$$S = \sum_i w_{ij} S(f_i) \tag{8}$$

7. All images in the database are arrange according to their similarity, then return the first N images which are most similar to the image user need.
8. For each of the retrieved object, the user marks it as relevant or irrelevant according to his information need.
9. The system updates the weights according to user's feedback opinion and go to step 2.

C. Updates Weight value according to User's Feedback

In the computer-based retrieval system, the expression and the weight value of image vision characteristic is definite, and in relevance feedback-based retrieval system, it is necessary to update the weight value dynamically, and express the rich image content by many kinds of characteristics expressions.
W_{ij} is corresponded to the weight of different characteristic vector, and it reflects the different attention to various characteristics in total similarity, the adjustment to W_{ij} may follow the formula hereinafter according to user's relevance feedback.

Let T is the aggregate of the first N images, which are the most similar ones that determined by the total similarity S. S_i is the relevance score feedback by the user.

$$S_i \begin{cases} = 3 & \text{Highly relevant} \\ = 1, & \text{Relevant} \\ = 0, & \text{No opinion} \\ = -1, & \text{Not relevant} \\ = -3, & \text{Highly not relevant} \end{cases} \quad (9)$$

For each r_{ij} set T_{ijo} be the most similar image search image, which determined according to $S(r_{ij})$, set $W_{ij} = 0$ and then adjust the weight as follows:

$$W_{ij} = \begin{cases} W_{ij} + S_i & \text{if } T_{ijo} \in T_M \\ W_{ij} & \text{Others} \end{cases} \quad (10)$$

Suppose that there are M images in the database, put the expression vectors r_{ij} of extremely related image together into a M x K matrix and each column of this matrix is a r_{ijk} sequence. The reciprocal of standard deviation of this sequence is preferable estimation to weight, $W_{ijk} = 1/\partial_{ijk}$.

VII. Experimental Analysis

Given an image query Q and an image database S, retrieve from S those images Q' which contain Q according to some notion of similarity. Figure 1 which displays an example query image and its relevant answer set. Figure 2 shows the image of such answer set and their respective answer rank retrieved within the top 10 matches.

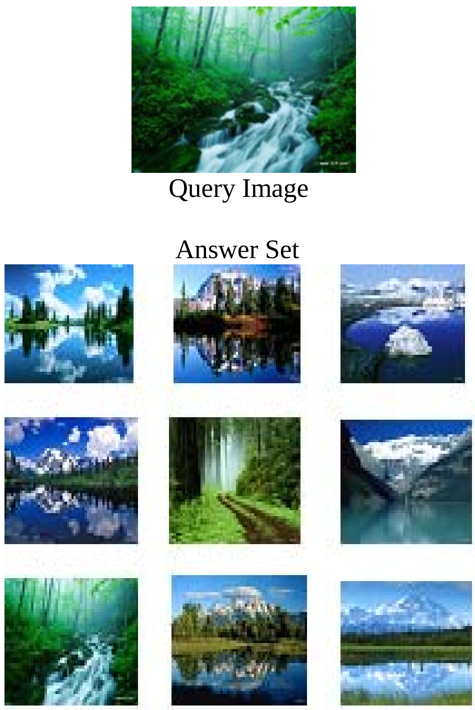

Fig. 2 A Query image and its relevant answer Set.

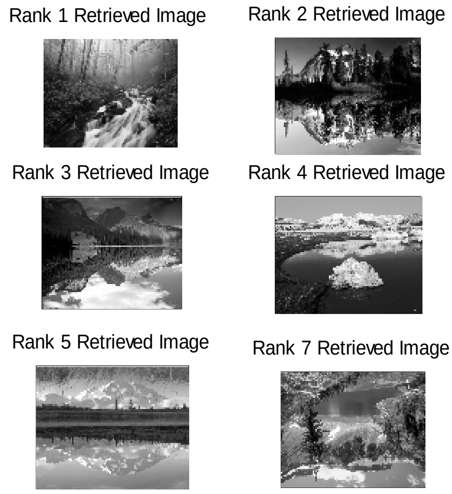

Fig. 3 Rank of the relevant images obtained.

VIII. Conclusions

Relevance feedback is a powerful technique in order to improve the performance of image retrieval. It is an open research area to the researcher to reduce the semantic gap between low-level features and high level concepts. In this paper we have shown, for the first time, how relevance feedback can be used to improve the performance of CBIR. We presented a relevance feedback based technique, which is based on re-weighting scheme that assigns penalties to each of database images and updates those of all relevant images using both the positive and negative examples identified by the user. The user's feed-back is used to refine the image similarity measure by weighting the distances between the query and the database image.

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