FCBIR: A Fuzzy Matching Technique for Content-Based Image Retrieval

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Abstract. Semantic image retrieval basically can be viewed as a pattern recognition problem. For human, pattern recognition is inherent in herself/himself by the inference rules through a long time experience. However, for computer, on the one hand, the simulated human identification of objects is impressive at its experience (training) like a baby learns to identify objects; on the other hand, the precise identification is unreasonable because the similar features are usually shared by different objects, e.g., "an white animal like cat and dog", "a structural transportation like car and truck". In traditional approaches, disambiguate the images by eliminating irrelevant semantics does not fit in with human behavior. Accordingly, the ambiguous concepts of each image estimated throughout the collaboration of similarity function and membership function is sensible. To this end, in this paper, we propose a novel fuzzy matching technique named *Fuzzy Content-Based Image Retrieval (FCBIR)* that primarily contains three characteristics: 1) conceptualize image automatically, 2) identify image roughly, and 3) retrieve image efficiently. Out of human perspective, experiments reveal that our proposed approach can bring out good results effectively and efficiently in terms of image retrieval.

Keywords: multimedia database, content-based image retrieval, data mining, fuzzy set, fuzzy search.

1 Introduction

A huge amount of images are generated in our everyday life as the fast growth of advanced digital capturing devices for multimedia, such as digital camera and mobile-photography phone. Through WWW, the collective image repository will be further bigger and bigger because of the speeding exchange of these life images. As a result, how to access the growing heterogeneous repositories effectively and efficiently has been becoming an attractive research topic for multimedia processing. Basically, semantic image retrieval can be viewed as a pattern recognition problem. For human, pattern recognition is inherent in herself/himself by the inference rules through a long time experience. However, for computer, it is hard to represent an image out of human aspect even though a number of researchers attempt to investigate a powerful identification algorithm from different visual viewpoints. It tells us the truth that there still exists a large improvement ground for image recognition. Classic approaches make use of image features like color, texture and shape to calculate the similarities among images, called visual-based or content-based image retrieval (CBIR). The

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main drawback of this-like approaches is that it is hard to represent the diverse concepts of an image just by a set of low-level visual features. To be closer to human sense, the other ways to connect human sense and machine cognition are classification and annotation, called textual-based image retrieval. Practically, both of classification and annotation put the focus on distinguishing the specific semantics of images by computing feature dissimilarities among them. Unfortunately, couples of objects (categories) in real world always share the same features and hence they are so difficult to be identified precisely. For example, yellow color and circle shape are shared by many objects like sun, egg yolk and etc. Accordingly, for computer, on the one hand, the simulated human identification of objects is impressive at its experience (training) like a baby learns to identify objects; on the other hand, the precise identification is unreasonable because the similar features are usually shared by different objects, e.g., "an white animal like cat and dog", "a structural transportation like car and truck". Besides, to raise the accuracy of image retrieval up, derivative complex computations will really damage the execution time, and the poor performance cannot satisfy user's requirement. Therefore, in this paper, we propose a novel fuzzy matching technique named *Fuzzy Content-Based Image Retrieval (FCBIR)* that primarily contains three characteristics: 1) conceptualize image automatically, 2) identify image roughly, and 3) retrieve image efficiently. The rest of this paper is organized as follows: Section 2 briefly describes the previous works on image retrieval. Section 3 introduces the proposed method in detail. Experiments on our approach are illustrated in Section 4 and conclusions and future work are stated in Section 5.

2 Related Work

Image retrieval has been a hot research issue for a long time because it can prevent the search from costing expensively by efficient image recognition. General visual-based similarity matching methods primarily take advantage of extracted features to accomplish the image retrieval, e.g., [12]. Unfortunately, this-like approaches cannot provide enough semantic support to help user get accurate results since visual features cannot supply common users sufficient information to identify the semantic they want. In addition, data mining is another way to make effective image retrieval. Chabane Djeraba [5] proposed an approach by using association mining [2] for content-based image retrieval. In this approach, it generates an efficient visual dictionary that summarizes the features in database. Each feature of visual dictionary associated with a symbolic representation help users find out the images effectively. The other way to reduce the gap between low-level features and high-level concepts is to let the images be with proper concepts, such as classification and annotation, e.g., [1][6][10][11]. Indeed, the mutual aim of existing approaches is to do image retrieval a good favor, but in vain. The similar experienced phenomenon also exists in most of the other AI research fields. The major reason is that the precise process is very difficult to deliver the exact concept in user's mind. Hence, fuzzy set theory has been adopted by more and more recent intelligent systems due to its simplicity and similarity to human reasoning [7][8]. FIRST (Fuzzy Image Retrieval SysTem) proposed by Krishnapuram *et al.* [9] uses Fuzzy Attributed Relational Graphs (FARGs) to represent images where each node in the graph represents an image region and each edge represents a relation between two regions. Every query is converted into a FARG to compare with the FARGs in the database. Chen *et al.* [4] proposed UFM (unified feature matching) to retrieve the images. In this study, an image is represented as several segmented regions based on a fuzzy feature. Nevertheless, the effects of above two fuzzy approaches are both on the foundation of segmented regions and the region segmentation still has not been very promising until now. Therefore, in this paper, we propose a new fuzzy matching technique to touch user's mind without region segmentation.

3 Proposed Approach: FCBIR

As mentioned above, the goal of our proposed approach is to make effective and efficient image retrieval with fuzzy human concept. To achieve this goal, we integrate similarity function and membership function to assist the fuzzy image retrieval, as shown in Figure 1. The major task of proposed approach can be briefly decomposed into three following subtasks.

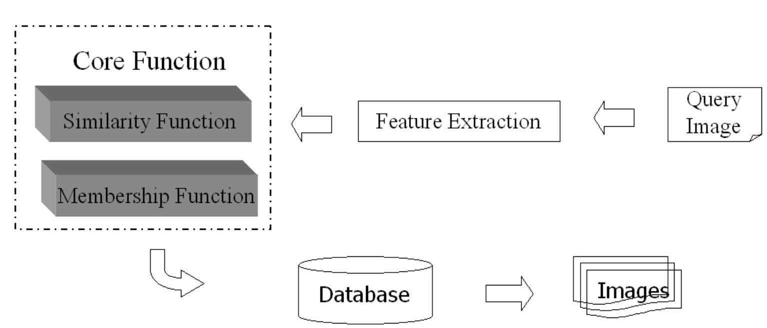

Fig. 1. The work flow diagram of FCBIR

I. Construction of Data Ontology: This phase involves some infrastructural works that include defining the data ontology, collecting all related images and clustering these collected images. In general, this phase can be regarded as an essential work for preprocessing images stored in the database.
II. Transformation of Fuzzy Sets: As those categorized images are clustered in above phase, similarity function and membership function will cooperate to let the images be with rough semantics in this phase.
III. Exploration of Images: Once the system receives a query submitted from user, the proposed matching algorithm performs a nice concept exploration of images. According to the specific concept picked by user, she/he thus can obtain the preferred images further.

In the followings, we will describe above works in great detail.

3.1 Construction of Data Ontology

Generally, this idea is motivated by natural human learning because the reason why humans can identify an object is that the viewed object can be identified by the similar objects of data ontology in her/his memory. Unlike traditional similarity matching approaches based on low-level features, the categorized images of pre-defining semantic ontology can actually facilitate the image concept retrieval like human learning. Hence, we take a look at the construction of data ontology in the beginning of designing this system. In this work, first, the frame of concept ontology has to be defined since it is projected on by the query images during the concept retrieval phase. As shown in Figure 2, it can be considered as a tree structure composing of hierarchical nodes structured by linguistic terms. Second, gather all categorized images belonging to each leaf node and store them into the database. In fact, without the exact collection, we cannot conceptualize the image excellently. Third, cluster the images of each category individually. More seriously, clustering is a fundamental but critical preprocessing operation for image identifications. In the third procedure, features, such as Color Layout, Color Structure, Edge Histogram, Homogeneous Texture and Region Shape, are extracted by the popular tool XMTool [3], and the similarities are generated by calculating Euclidean Distance d of v to u ($d = \sqrt{\sum_{i=1}^{n}(v_i - u_i)^2}$, where n is the number of feature vectors) during the clustering period. At last, the images of each category are clustered into equalized groups by famous cluster algorithm k-means. Its physical meaning is that we can discover the images with the same semantic but different views. For example, a category "car" usually contains different visual features like "color", "texture" and "shape", and each car may be with different visual properties like "front-view", "back-view" and "side-view".

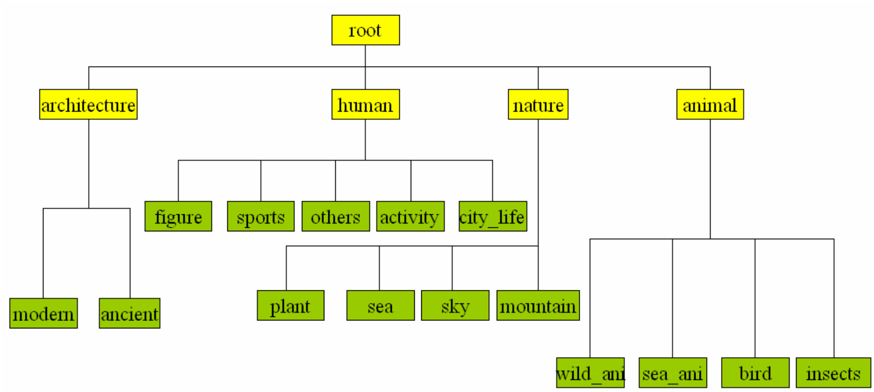

Fig. 2. Example of data ontology

Due to clustering operation does make a significant impact on the accuracy for both conceptualizing and exploiting the images, one of the important issues in our proposed method is the quality of clustering. Thus, we employ three measures to make the validation for clustering quality.

Local Density: Local Density is the density of each cluster. It delivers the entropy of each cluster. A cluster with lower density shows us a poor clustering effect because most of points in this cluster are very dissimilar.

Global Density: Global Density is the density of all clusters in the global space. In contrast with local density, good cluster dispersion is with a longer average distance among global clusters.

Local Proportion: In order to reach the presetting quantity of clusters, thereby the cardinality of images of each cluster will not be the same. The higher local proportion represents a reliable quality of clustering.

On the basis of above, we can set three thresholds to ensure the clustering being good enough to offer sufficient support for the following tasks described in the next two subsections. That is, the clustering algorithm ends while three thresholds are all satisfied.

As described above, a cluster for each category can be considered as a view with the visual-distinguishability property. Another crucial issue in this step is how to generate the sample-image for each cluster. Given $N = \{ca_1, ca_2, \ldots., ca_i\}$ denotes a set of categories and $CL_{ca_i} = \{cl_1, cl_2, \ldots., cl_j\}$ denotes a set of clusters belonging to the category ca_i, and each cluster contains m images $cl_j=\{I_1, I_2, \ldots., I_m\}$. Then the sample-image of cl_j, $SMMG$, is defined as:

$$SMMG_{cl_j}(C,S,T) = \left(\frac{\sum_{x=1}^{m} C_x}{m}, \frac{\sum_{y=1}^{m} S_y}{m}, \frac{\sum_{z=1}^{m} T_z}{m}\right) \tag{1}$$

where $\{C, S, T\}$ represents the feature set {color, shape, texture}. After calculating the *SMMG*, we can find out the sample-image of each cluster of each category. Once the sample-images are identified, the images in the database are easy to be conceptualized by projecting them onto the concept ontology with computing the minimized similarities to these clusters.

3.2 Transformation of Fuzzy Sets

Actually, the images that are conceptualized with some rough semantics in this phase will enable the retrieval to be closer to human sense. In traditional approaches, disambiguate the images by eliminating irrelevant semantics does not fit in with human behavior. For example, some objects we never see possibly get couples of linguistic terms. To this end, the ambiguous concepts of each image estimated throughout the collaboration of similarity function and membership function in this phase is sensible. As shown in Figure 3, the whole process of Algorithm Trans_Fset for transformation of fuzzy sets can be elaborated on two following steps.

I. Similarity Calculation: In line 3 of Algorithm Trans_Fset, similarity mainly depends on computing the distance between an image and the sample-images of each cluster of each category. Accordingly, the processed image can pertain to some semantics with respect to the clusters that are with shorter distances derived from the above similarity function. For example, assume that k is 20. An image with four relevant concepts can be represented as {(animal, 7), (insect, 3), (building, 5), (plant, 5)} after the similarity calculations.

Input: The images in database D, predefined categories with grouped clusters, a set of membership functions
Output: Table T containing images with fuzzy sets
1. Define cardinality k;
2. **for** each image $I_j \in D$ **do**
3. Calculate distances and discover the top k closer clusters;
4. Calculate the count cnt_{ca_i} $(0 \le cnt_{ca_i} \le k)$ of each category ca_i from closer k clusters;
5. **for** each category with $cnt_{ca_i} \neq 0$ **do**
6. Convert cnt_{ca_i} of ca_i into a fuzzy set $f^j_{ca_i}$ denoted as $\left(\frac{M_1^{ca_i}}{R_1^{ca_i}} + \frac{M_2^{ca_i}}{R_2^{ca_i}} + ... + \frac{M_n^{ca_i}}{R_n^{ca_i}}\right)$ by employing the given membership functions, where $R_n^{ca_i}$ is the n^{th} fuzzy region of ca_i and $M_n^{ca_i}$ is the fuzzy membership value in region $R_n^{ca_i}$;
7. $F^j = \cup f^j_{ca_i}$;
8. **end for**
9. $T = \cup F^j$;
10. **end for**
11. **return** T

Fig. 3. Algorithm Trans_Fset

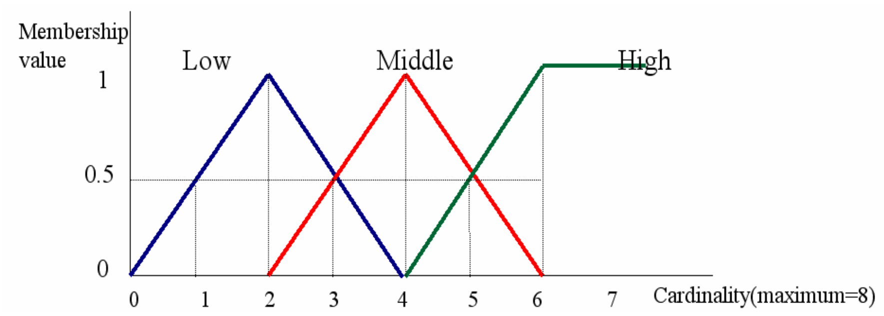

Fig. 4. Fuzzy membership functions for cardinality attribute

II. Fuzzy Set Transformation: After similarity calculations, the fuzzy sets of each image in the database can be implied by our proposed membership functions based on [7], and from line 4 to line 9 of Algorithm Trans_Fset, the transaction table T will soon be yielded by these fuzzified images. For example as above, the third concept (building, 5) of an image can be converted into the fuzzy set ($\frac{0.0}{building.low}+\frac{0.5}{building.middle}+\frac{0.5}{building.high}$) by employing the given membership functions as shown in Figure 4. The whole procedure ends while all the concepts in each image are converted into fuzzy sets. In our proposed membership functions, cardinalities are represented by three fuzzy regions: *Low*, *Middle* and *High*. Thus, *concept.term* is called a fuzzy region.

3.3 Exploration of Images

As the fuzzilized table being ready, the system will perform image search algorithm described in this subsection. This phase generally concerns the procedure that starts with while the image queried by user, the system first analyzes the query image by similarity function and membership function. Then the query image with fuzzy sets will be compared with the fuzzilized images in the database by executing the proposed matching algorithm FIM, as shown in Figure 5. At last, the system responses the ranking images for each related concept. In detail, if FIM finds out the images with fuzzy regions fully hit by the query, the most similar images for each related concept are selected. Otherwise, the top-m images with fuzzy regions partially hit by the query will be filtered by *I_SIM* and *I_DISIM* described as follows. That is to say, the top-m images are mainly selected by the higher *I_SIM*, and if the images with the same *I_SIM*, those with higher *I_DISIM* will be discarded further. Finally, the referred concepts can be derived from these selected images by using *C_SIM*.

As stated above, in this algorithm, three main functions that are devoted to calculate image similarity and concept similarity will be described below. Assume that the amount of the images with full-hit fuzzy sets to the query for category ca_i is N_{ca_i} and the amount of the images for category ca_i is Q_{ca_i}, then the similarity of the query image to ca_i is:

$$C\_SIM_{ca_i} = \frac{N_{ca_i}}{Q_{ca_i}}, \tag{2}$$

and given that the j^{th} image $I_j \in D$ with the fuzzy sets I_j={{*same*}, {*diff*}}, where *same* is a set consisting of the same *sr* fuzzy regions to the query image and *diff* is a set consisting of different *dr* fuzzy regions to the query image, $diff = I_j \backslash same$, then the similarity of the query image to I_j is:

$$SIM_{I_j} = \sum_{sr=1}^{|same|} membership(sr), \tag{3}$$

and the dissimilarity is:

$$DISIMI_j = \sum_{dr=1}^{|diff|} membership(dr) \tag{4}$$

Apart from *C_SIM*, in order to capture higher-level concepts of the concept ontology, we can further compute the accumulated similarities of higher-level concepts to the query image by the following equation.

$$HC\_SIM_l = \frac{\sum_{i=1}^{|HC_l|} C\_SIM_{ca_i}}{|HC_l|} \tag{5}$$

where HC_l is l^{th} higher-level concept that is the ancestor of the category ca_i.

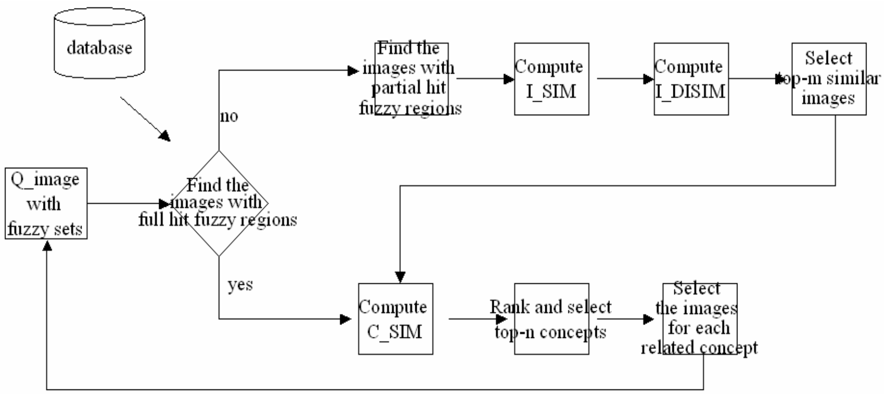

Fig. 5. Algorithm FIM (Fuzzy Image Matching)

4 Experimental Evaluation

In previous section, we have expressed the proposed approach for fuzzy content-based image retrieval. Now we describe the prototype of this system and the results in evaluating the performance of proposed method by experiments using real image data. As shown in Figure 2, there were 36867 images collected from Corel spreads in 15 categories that vary in amounts, and each category is grouped into 8 clusters. Figure 6 depicts the system prototype. In this interface, the query image displayed on the top of the left frame is detected for several ranking concepts, and the referred higher-level concepts are displayed at the bottom of the left frame. This query image is originally classified into concept “activity”. In traditional approaches, its implicit concepts, such as “sea”, “sports”, “human” and “nature”, are hard to be estimated, but our proposed approach comparatively can catch these hidden concepts. Out of these implied concepts, the most similar images of top-5 concepts are shown in the right frame. User can further pick the preferable concepts or images by clicking them. Every picked concept will represent the most similar 20 images to the query. Regarding our experiments, most of images can be detected for its correct concept or higher-level concepts. Even more implicit reasonable concepts can be also found. Furthermore, we

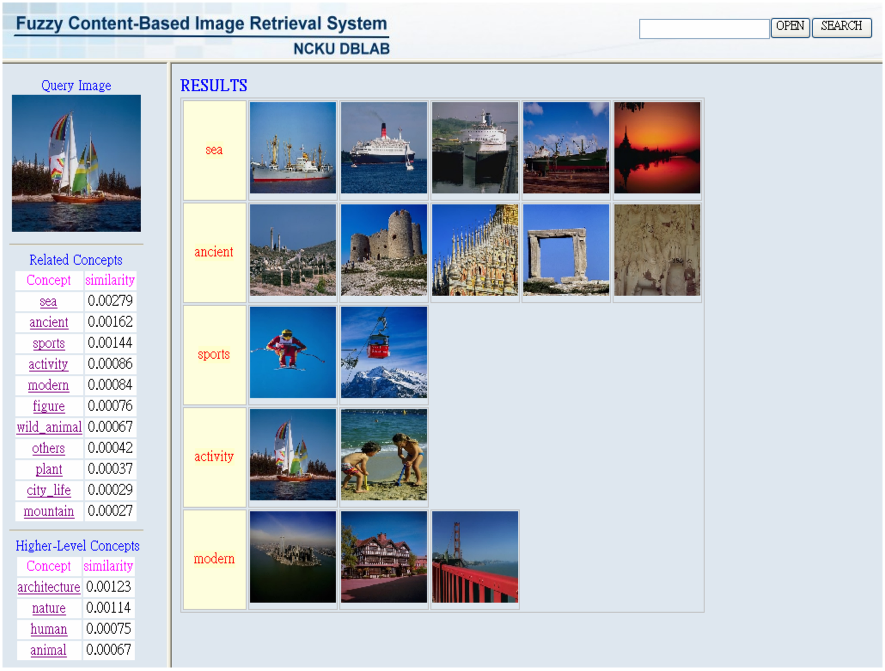

Fig. 6. Example of query results

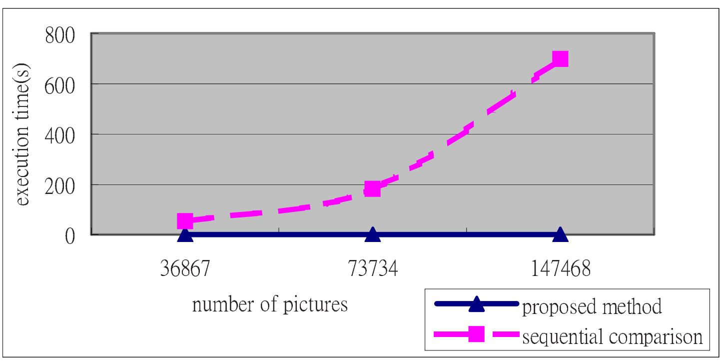

Fig. 7. Execution efficiency for image search

doubled and tripled the population of original images to evaluate its performance. In this experiment, the fuzzy sets of all images for our proposed approach are pre-generated and stored into SQL server in advance, and the features of those for sequential comparison approach are pre-extracted and stored in a feature vector list. Figure 7 illustrates that the performance of our proposed approach outperforms the sequential comparison approach significantly in terms of execution time.

5 Conclusions and Future Work

In this paper, we have represented a new fuzzy matching technique for content-based image retrieval by combining visual features and fuzzy sets. The rough concepts mined exhibits a reasonable machine learning from human aspect, and moreover it can furnish a great support to assist a common user in exploring the images from a large-scale database effectively and efficiently. Without additional segmentation operation and sequential comparison, membership function can facilitate the rough concept search together with similarity function. In the future, we will further keep an eye on the relevance feedback and develop an effective approach for the interaction with user during the retrieval phase. Besides, investigate optimal settings about cluster number, *k* clusters closer to the query, similarity function and membership functions is another critical issue that perhaps can bring out a better result.

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