

# Object-Based Image Retrieval System Based On Rough Set Theory

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## Summary

The goal of this paper is to create image retrieval system based on image objects. In the context of Rough Set Theory we introduce an accurate Object-Based Image Retrieval (OBIR) system that can handle image-based queries, and presents an efficient algorithm to retrieve images from large databases, by defining novel image feature called *Object Similarity Ratio* used in the proposed system.

## Key words:

Rough set theory, Image retrieval, Object-oriented image analysis.

## 1. Introduction

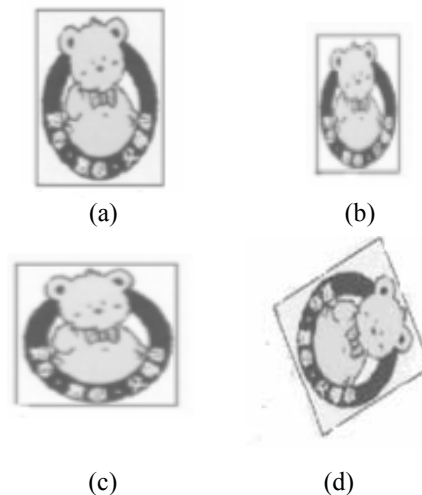
Many people have started to work with different applications in the multimedia field, generating huge databases of multimedia information (such as images, videos, etc).

This information needs to be accessed by other applications or users. To support this issue, new fields of research have appeared. For instance, the one that involves access to static images in databases is known as image retrieval. Image retrieval systems are defined as those systems that find all images in a given database depicting scenes of some specified type. This type is usually given (pre-selected) by a supervisor or user. These user specifications are known as queries [5].

Image retrieval systems attempt to search through a database to find images that are perceptually similar to a query image. Image retrieval algorithms roughly belong to two categories: text-based approaches and content-based methods. Content Based Image Retrieval (CBIR) is an important alternative and complement to traditional text-based image searching and can greatly enhance the accuracy of the information returned. It aims to develop visual-content-based technique to search, browse and retrieve relevant images from large-scale digital image collections. Most proposed CBIR techniques automatically extract low-level features (for example. color, texture, shapes of objects and spatial layout) to measure the similarities among images by comparing the feature differences [2].

However, we know that there is an obvious semantic gap between what user-queries represent based on the low-level image features and what the users think. To overcome the semantic gap, many researchers have investigated techniques that retain some degree of human intervention either during input or search thereby utilizing human semantics, knowledge, and recognition ability effectively for semantic retrieval. These techniques called Object-Based Image Retrieval OBIR [4].

The proposed system is applied on image database with single centered object images. The expected output is a set of images from the input database each of which contains an object that is most similar to the query image. Object may appear on database images at different locations with varied sizes. For instance, figure (1) shows a query image and the target database images that contain shift, scale, and rotation variations and object of interest encircled by circle. An excellent image retrieval method should be insensitive to these variations [1].



**Fig ( 1):** a) A query image and the target database images with (b) scale, (c) shift and (d) rotation variant images.

The OBIR technique can be used in many application fields such as medical image archiving, computer aided design, and geographic information systems.

This paper is organized as follows: In section 2, a brief overview of OBIR system is introduced. In section 3, rough set theory preliminaries and image modeling with rough sets is presented. Section 4 shows the overall architecture of the proposed system. Experiments and results are discussed in Section 5. Section 6 presents performance evaluation for the retrieval. Finally conclusions are introduced in section 7.

## 2. A brief overview of OBIR

OBIR systems retrieve images from a database based on the appearance of physical objects in those images. These objects can be elephants, stop signs, helicopters, buildings, or any other object that the user wishes to find where an object in image tends to satisfy the following conditions as given in [3].

- (1) It is located near center of the image,
- (2) It has significant color or texture characteristics against its background,
- (3) Its size is relatively big,
- (4) Its boundary pixels have relatively strong edginess,

One common way to search for objects in images is to first segment the images in the database and then compare object region to object region in some query image presented by the user. Such image retrieval systems are generally successful for objects that can be easily separated from the background and that have distinctive colors or textures.

### Image Segmentation

Image segmentation is one of the most challenging tasks in image processing and is a very important pre-processing step in the problems in the area of image analysis, computer vision, and pattern recognition. In many applications, the quality of final object classification and scene interpretation depends largely on the quality of the segmented output. Large number of segmentation algorithms is presented, but there is no single algorithm that can be considered good for all images [6].

The basic processing units in OBIR are objects. With object-oriented approach to analyze image, the first step is to always form the processing units by image segmentation. Segmentation refers to the process of partitioning a digital image into multiple non overlapping homogeneous regions, where the homogeneity of a region may be composed based on different criteria such as gray level [6]. Thus the goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.

In gray scale images boundaries between objects are often ill defined because of grayness and/or spatial ambiguities. This uncertainty can be handled by describing the different objects as rough sets. The rough set theory has become a popular mathematical tool for ambiguity caused by limited discernibility of objects in the domain of discourse [8].

## 3. Rough Set Theory Preliminaries

Rough set theory depends on the idea that every object of interest is associated with a piece of knowledge indicating relative membership. Knowledge is represented by means of a table, so-called an information system, where rows and columns respectively denote objects and attributes. An information system,  $S$ , is given as a pair  $S = (U, A)$  where  $U$  is a non-empty finite set of objects, as the universe, and  $A$  is a non-empty finite set of attributes. Let  $B \subseteq A$  and  $X \subseteq U$ . We can approximate the set  $X$  using only the information contained in  $B$  by constructing the lower and upper approximations of  $X$ . If  $X \subseteq U$ , the sets  $\{x \in U : [x]_B \subseteq X\}$  and  $\{x \in U : [x]_B \cap X \neq \Phi\}$ , where  $[x]_B$  denotes the granule in other words equivalence class of the object  $x \in U$  relative to the equivalence relation  $I_B$ , are called the  $B$ -lower and  $B$ -upper approximations of  $X$  in  $U$ . They are denoted by  $\underline{B}X$  and  $\overline{B}X$ , respectively. The objects in  $\underline{B}X$  can be certainly classified as members of  $X$  on the basis of knowledge in  $B$ , while objects in  $\overline{B}X$  can only be classified as possible members of  $X$  on the basis of  $B$  [7].

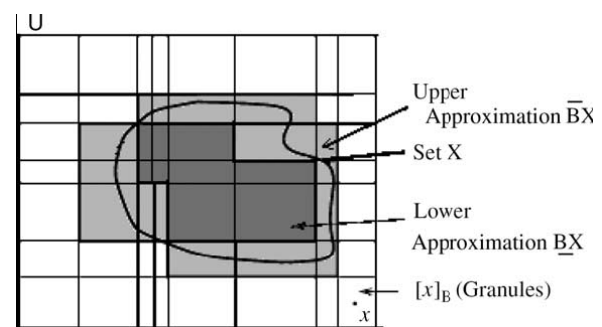


Fig (2): Rough representation of a set  $X$  with its upper and lower approximations.

These are illustrated in figure (2) where the sets of dark-gray granules represent lower approximation, while those of both dark-gray and light-gray granules together denote upper approximation.

The roughness of a set  $X$  with respect to  $B$  can be characterized numerically as  $R_{\alpha} = 1 - \frac{|BX|}{|B|}$ . This means

if roughness of the set  $X$  is 0 then  $X$  is crisp with respect to  $B$ , and if  $R_{\alpha} > 0$  then  $X$  is rough [8].

Let the universe  $U$  be an image consisting of a collection of pixels. Then if we partition  $U$  into a collection of non-overlapping windows (of size  $m \times n$ , say), each window can be considered as a granule  $G$ . A granule is a clump of pixels in the universe of discourse; drawn together by indistinguishability, similarity, proximity, or functionality. Thus granulation involves decomposition of whole into parts [9].

Let us consider an object-background separation (a two class) problem of an  $m \times n$  gray scaled image with gray level intervals  $(0, 1, \dots, T, T+1, \dots, L-1)$  with  $L$  gray levels; Let  $B$  and  $O$  represent two properties that characterize background and object regions, respectively. Object and background can be viewed as two sets with their rough representation with respect to gray level  $T$  is given in [7] as follows:

Lower approximations of the object ( $\underline{O}_T$ ):

$\underline{O}_T = \{\bigcup_i G_i \mid P_j > T, \forall j = 1, \dots, mn, \text{ and } P_j \text{ is a pixel belonging to } G_i\}$ .

Upper approximation of the object ( $\overline{O}_T$ ):

$\overline{O}_T = \{\bigcup_i G_i, \exists j, j = 1, \dots, mn \text{ s.t. } P_j > T, \text{ where } P_j \text{ is a pixel in } G_i\}$ .

Lower approximations of the background ( $\underline{B}_T$ ):

$\underline{B}_T = \{\bigcup_i G_i \mid P_j \leq T, \forall j = 1, \dots, mn, \text{ and } P_j \text{ is a pixel belonging to } G_i\}$ .

Upper approximations of the background ( $\overline{B}_T$ ):

$\overline{B}_T = \{\bigcup_i G_i, \exists j, j = 1, \dots, mn, \text{ s.t. } P_j \leq T, \text{ where } P_j \text{ is a pixel in } G_i\}$ .

Therefore, the rough set representation of the image (object  $O_T$  and background  $B_T$ ) depends on the gray level value  $T$ .

Inexactness of a set is due to the existence of a borderline which is obtained from the difference between upper approximation and lower approximation. Thus the roughness of object  $O_T$  is given by:

$$R_{O_T} = 1 - \frac{|\underline{O}_T|}{|\overline{O}_T|} = \frac{|\overline{O}_T| - |\underline{O}_T|}{|\overline{O}_T|} \quad (1)$$

where  $|\underline{O}_T|$  and  $|\overline{O}_T|$  are the cardinality of the sets  $\underline{O}_T$  and  $\overline{O}_T$  resp.,

Similarly, the roughness of background  $B_T$  is given by:

$$R_{B_T} = 1 - \frac{|\underline{B}_T|}{|\overline{B}_T|} = \frac{|\overline{B}_T| - |\underline{B}_T|}{|\overline{B}_T|} \quad (2)$$

where  $|\underline{B}_T|$  and  $|\overline{B}_T|$  are the cardinality of the sets  $\underline{B}_T$  and  $\overline{B}_T$  resp.,

We proposed a measure called "mean roughness measure"  $RM_T$  for an image, which denotes the average of roughness of object  $R_{O_T}$  and background  $R_{B_T}$  at a certain threshold  $T$ , as defined in equation (3) [9].

$$RM_T = \frac{R_{O_T} + R_{B_T}}{2} \quad (3)$$

From equation (1) and equation (2) we can deduce that the value of  $RM_T$  lies between 0 and 1 because  $0 \leq R_{O_T} \leq 1$  and  $0 \leq R_{B_T} \leq 1$ .  $RM_T$  has a maximum value of unity when  $R_{O_T}$  and  $R_{B_T}$  equal one, and minimum value of zero when  $R_{O_T}$  and  $R_{B_T}$  equal zero. Similarly the value of  $RM_T$  determines the roughness of the region determined.

Let us describe a method for object enhancement/extraction based segmentation using the principle of minimizing  $RM_T$  for different granule size. Minimizing of  $RM_T$  minimizes the uncertainty arising from vagueness of the boundary region of the object. Therefore, for a given granule size, the threshold for object-background classification can be obtained through minimizing  $RM_T$ . This is done by computing the  $RM_T$  of the image for every gray level  $T$ , representing the background and object regions  $(0, \dots, T)$  and  $(T+1, \dots, L-1)$ , respectively, and select the one for which  $RM_T$  is minimum. In other words, select  $T^* = \arg \min_T RM_T$  as the optimum threshold to provide the object-background segmentation.

#### 4. Architecture of The Proposed System

In order to retrieve the similar images to the user query, at first user enter the query image. Then its object is

extracted, by computing object\_lower approximation array according to optimal threshold  $T^*$  using the algorithm given in [9]. To match between two objects in two different images we compare between object\_lower approximation array of the two images. In the proposed method we compare between object\_lower approximation array of the query image, and object\_lower approximation array of each image in the input image database.

Compute the number ( $N$ ) of the pixels that has the similar values in the two arrays. Then the Object Similarity ratio is calculated for each image database such that

$$\text{Object Similarity Ratio (R)} = \frac{N}{T} \quad (4)$$

Where  $N$  is the number of pixels which have the same value in two object\_lower approximation array of images (query image and database image) and  $T$  is the size of object\_lower approximation array.

We find that, Object Similarity Ratio takes the values  $0 < P \leq 1$ , where  $P$  equal one if two compared images are the same. Consequently, the proposed system retrieves the images that have object similarity ratio value approximately equals 1. It sorts descending the images database according to Object Similarity Ratio and retrieve the first four images according to user's choice. Figure (3) shows the sorted database according to Object Similarity Ratio resulted from a case study of searching the shown image within an image database consisting of 51 objects.

| ID  | Object Similarity Ratio |
|-----|-------------------------|
| 13  | 0.924072265             |
| 15  | 0.92224121              |
| 14  | 0.921325683             |
| 51  | 0.921325683             |
| 17  | 0.921203613             |
| 16  | 0.921081542             |
| ... | ...                     |
| 38  | 0.897094726             |
| 20  | 0.85583496              |
| 23  | 0.844787597             |
| 51  |                         |

→ Load image 13




Fig (3): shows the sorted database according to Object Similarity Ratio

#### 4.2 Object -Based Image Retrieval Framework:

A block diagram represents our proposed approach to OBIR system is shown in Figure (4). In this proposed system, the relevance between a query and any target image is ranked according to a similarity measure. The similarity comparison is performed based on object that appears in the images.

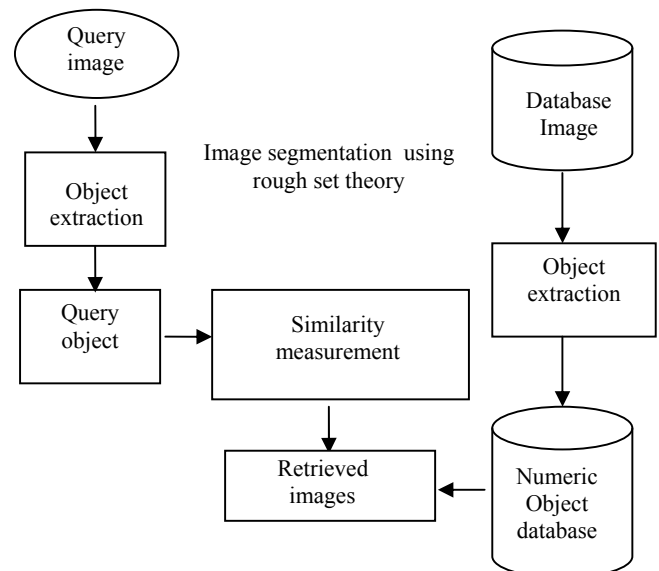


Fig (4): Proposed scheme for object-based image retrieval system

#### 4.3 The Proposed Algorithm of Retrieval System

**Input:** Gray scaled image with one centered object.

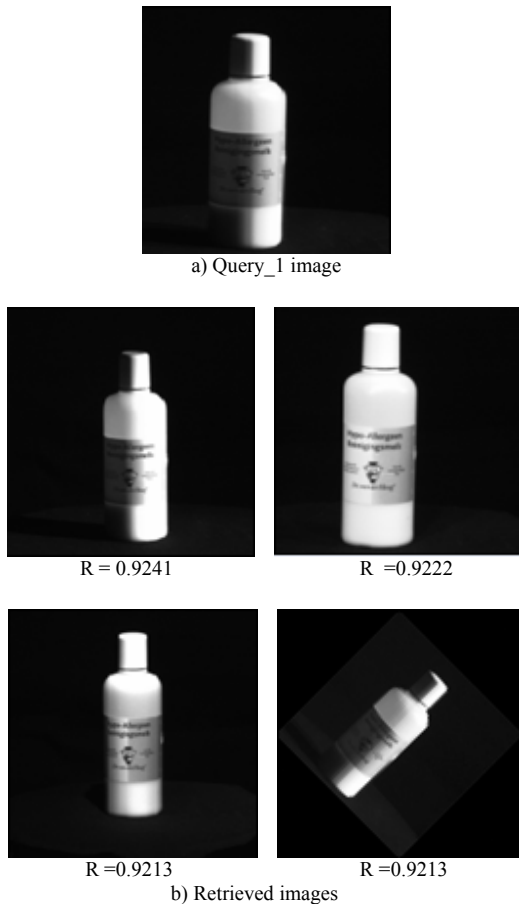
**Output:** Optimal similar image.

**Method:**

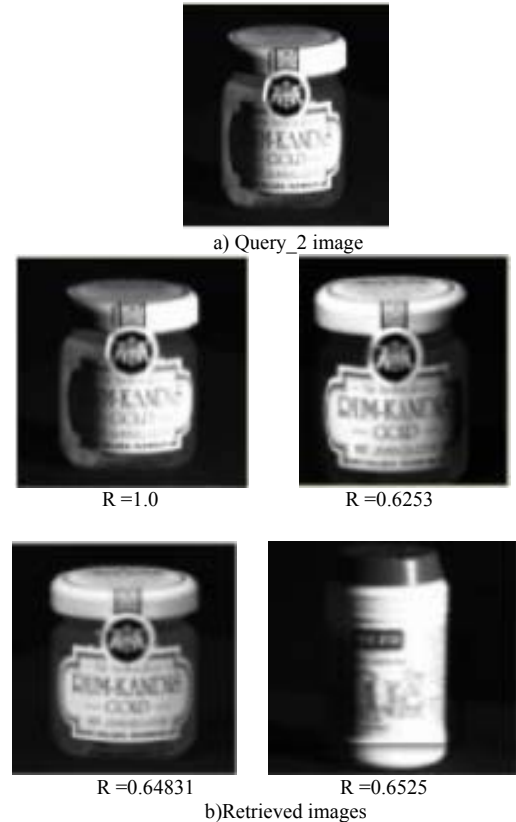
- Construct image Database using Microsoft access.
- Store the images in the database.
- Store object\_lower approximation array according to optimal-threshold  $T^*$  for each image in database.
- Calculate object\_lower approximation array according to optimal-threshold  $T^*$  for query image that selected by user.
- Compare the object\_lower approximation array of query image with object\_lower approximation array of each image in database table.
- Find the Object Similarity Ratio for each image in image database by using the equation (4).
- The images with largest Object Similarity Ratio are retrieved from database; the number of retrieved images is specified by user.

## 5. Experiment and Result

Our experiment and results are running under Processor: P4 with 2 GB RAM and MatLab version 7.0 using Database toolbox. To test our algorithm, a collection of 51 grayscale images of size 128x128 was processed, where every image has a unique centered object. To evaluate the performance of our system, we performed this experiment. The proposed system is implemented under the Windows XP operating system. When the user enter query image the proposed system retrieves the images that have Object Similarity Ratio value approximately equals 1. It sorts the images database descendingly according to *Object Similarity Ratio* and retrieves the first four images according to user's choice. The image database is selected from the gallery, which is a collection of professional photos web image sited on, <http://www.cs.cmu.edu/~cil/v-images.html>. The retrieval result are illustrated in figure (5) and figure (6).



**Fig(5):** Retrieval results for Query\_1  
a) input image b) retrieved images depending on Object Similarity Ratio (R)



**Fig (6):** Retrieval results of Query\_2  
a) Input query image, b) retrieved images depending on Object Similarity Ratio (R)

It is clear that on running the proposed system on single objects images, the first retrieved image is optimal image because it has the largest value of *Object Similarity Ratio*

## 6. Performance Evaluation for the Retrieval

Usually precision and recall are used in retrieval system to measure retrieval performance. Precision ( $P_r$ ) is defined as the ratio of the number of relevant images retrieved ( $N_r$ ) to the number of total retrieved images  $K$ . Recall ( $R_e$ ) is defined as the number of retrieved relevant images  $N_r$  over the total number of relevant images available in the database  $N_t$ .

$$R_e = N_r / N_t, \quad P_r = N_r / K.$$

It is ideal to have both high recall and precision.

Table (1) displays results for retrieval measured in terms of recall ( $R_e$ ), precision ( $P_r$ ).

**Table 1:** Show the result of retrieval system

| Query<br>image | Nt, K, Nr | Re   | Pr   | average |
|----------------|-----------|------|------|---------|
| Query1         | 50, 4, 4  | 0.08 | 1.0  | 0.540   |
| Query2         | 50, 4, 3  | 0.06 | 0.75 | 0.405   |

Therefore, from precision-recall measure for all query images, we find that, the value of  $R_e$  and  $R_r$  depend on number of relevant images retrieved (the value of  $N_r$ ), for constant value of  $N_t$ ,  $K$  such that  $N_t$  is number of all images in the database, and  $K$  is number of retrieval images which specify by user.

## 7. Conclusions

The traditional image retrieval mainly depends on color, texture and shape. For these basic visual features are just parts of image information, the retrieval results are not so perfect. This paper introduces a new method for object-based image retrieval that the Object Similarity Ratio as new features in the domain of the database. It presents an algorithm for accurate image retrieval in the context of rough set theory. The proposed system is not sensitive to the scale, shift, and rotation variances. Also the time of retrieval is very small.

## 8. References

- [1] Chan, Y., Ho, Y., Liu, Y. and Chen, R., *A ROI image retrieval method based on CVAAO*, Image and Vision Computing, pp. 1540–1549, 2008.
- [2] Dong-cheng, S., Lan, X. and Ling-yan, H., *Image retrieval using both color and texture features*, The Journal of China Universities of Posts and Telecommunications, Vol. 14, Sup. 1, pp. 94-99, 2007.
- [3] Hoiem, D., Sukthankar, R., Schneiderman, H., and Huston, L., *Object-Based Image Retrieval Using the Statistical Structure of Images*. IEEE Conference on Computer Vision and Pattern Recognition, Vol. 2, June, pp. 490 - 497, 2004
- [4] Kim, S., Park, S., and Kim, M., *Image Classification into Object/Non-object Classes*, Lecture notes in Computer Science, pp. 2056–2057, 2004.
- [5] Martinez, A. M. and Serra, J. R., *A New Approach to Object-Related Image Retrieval*, Journal of Visual Languages and Computing, pp 345–363, 2000
- [6] Mushrif, M. M. and Ray, A. K., *Color Image Segmentation: Rough-set Theoretic Approach*. Pattern Recognition Letters (29), pp.483–493, 2007
- [7] Pal, S. K., Uma S. B. and Mitra, P., *Granular computing, rough entropy and object extraction*, Pattern Recognition Letters 26, pp. 2509–2517, 2005.
- [8] Pawlak, Z., *Rough Sets, Theoretical Aspects of Reasoning about Data*. Kluwer Academic publ., 1991
- [9] Sharaway, G. A., Gomaa, M. A., and Ghali, N. I., and Ghoneim, W. A., *Object-Oriented Image Segmentation in Presence of Uncertainty*, Advances in Fuzzy sets and Systems, Vol. 3(3), pp.367-377, 2008.



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