Journal of Engineering Sciences, Assiut University, Vol. 40, No. 3, pp. 819-832, May 2012

REGION-BASED IMAGE RETRIEVAL WITH RELEVANCE FEEDBACK

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(Received January 2, 2012 Accepted February 29, 2012)

Region-based image retrieval (RBIR), a special type of content based image retrieval (CBIR), is an important research. This paper presents integration of RBIR with relevance feedback (RF) to enhance the performance of CBIR. Watershed algorithm is used to extract regions but not all regions are with the same importance. So, a region-weighting scheme reflecting the process of human visual perception is proposed. By using relevance feedback method, the matching process could improve retrieval performance interactively and allow progressive refinement of query results according to the user's feedback action.

KEYWORDS: *Relevance feedback; Region-based image retrieval; Content-based image retrieval; Attention center; Integrated region matching; Watershed segmentation; Feature extraction*

I. INTRODUCTION

With the growth of image databases and cheap digital storage, content based image retrieval (CBIR) has become an active research area during the past decade. CBIR [1] is a powerful tool for search engines since it simply helps retrieval of images similar to a query image based on their content. CBIR systems such as (QBIS, Photobook, MARS, PicToSeek, VisualSEEk) represent images using extracted visual features, such as color [2], shape [4] and texture [3] to represent and index the image.

According to [5], one of the main challenges is the semantic gap between users' high-level query concepts and low-level features which can be extracted.

In general, two approaches are commonly employed to solve the semantic gap problem. The first approach is to change the focus from the global content description of images into the local content description by regions (region-based image retrieval) or even the objects in images (object-based image retrieval) [12:18]. Regions are used to represent and index images in RBIR. Then the performance of a region-based image retrieval system is dependent on the method used to compare the two images, i.e. the performance is determined by the definition of similarity which is applied when performing the image similarity measurement.

To ensure robustness against inaccurate segmentation, several image-to-image similarity measurements, which combine the information from all regions of the two images, have been proposed. The integrated region matching (IRM) algorithm [6] performs a region-based retrieval process in which images are segmented by their color, texture and shape features, and a region of one image is then matched to several regions of the second image. In the IRM approach, the similarity measure was determined by the weighted sum of distance.

The second approach taken to reduce the gap between the high-level semantic concepts and the low-level image features involves the use of relevance feedback. This approach employs an online learning scheme to improve the retrieval extraction performance by applying relevant feedback according to the user's subjective perception. User provides his feedback by marking whether the retrieved images are relevant to the query or not. Based on the feedback, the system applies many different learning mechanisms. As short term (or session-based) feedback is applied at the end of any user session, also a long-term feedback is applied to incorporate accumulated feedback information.

The organization of the paper is as follows: Section II presents a brief overview of the proposed system. Section III presents the related work of RBIR. Section IV describes the representation of images based on image segmentation. Section V describes feature extraction and introduces a new region weighting method and a new region filtering method. In section VI, the design of the image similarity measure, based on IRM is presented. In section VII, the relevance feedback technique is described. Section VIII provides experimental results that evaluate all aspects of the proposed system. In section IX, conclusion with a discussion of the future work is presented.

II. SYSTEM OVERVIEW

Figure 1 presents a flowchart of the proposed system. As shown, the system comprises two major modules: an offline module and an online module. During the offline module, the system segments every image into different regions using watershed segmentation algorithm [7] and then extracts low-level features such as (color, texture and shape features) and region weights such as (close to center – size). All images names, region number and features of each region are stored in log file.

During the online module, when a query image is supplied by the user, all of the images are sorted according to their similarities to the query image according to IRM algorithm. In calculating distance, each dimension of the region feature is normalized to the range [0, 1] in order to prevent a dimension with large value from dominating the others.

If the user is unsatisfied with the retrieval results, he or she can specify the feedbacks to use in refining the results in the next iteration by marking relevant or irrelevant for each image. After user is satisfied with the retrieval result, the user updates the feature weight in the log file.

III. RELATED WORK

This section focuses on the previous researches over the two subjects, region based image retrieval, relevance feedback. Most of the existing region-based approaches can be classified based on four criteria: (1) the segmentation scheme; (2) the selected features for region description; (3) the region matching method; (4) how to enhance retrieval performance by interacting with a user.

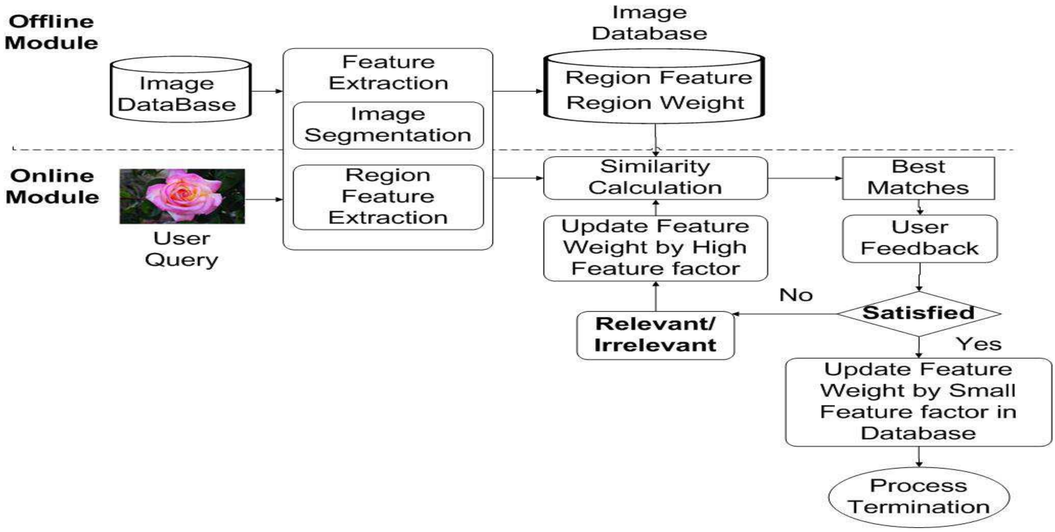


Figure 1.Flowchart of the proposed system.

In [15], System finds the dominant foreground region and finds the semantic category of that image. In [13], an approach is proposed that employs a fully unsupervised segmentation algorithm and associates low-level descriptors with appropriate qualitative intermediate-level descriptors, which form a simple vocabulary termed object ontology. Following that, a relevance feedback mechanism is invoked to rank the remaining, potentially relevant image regions and produce the final query results. The research work in [14] proposed an image retrieval framework that integrates efficient region based representation and effective on-line learning capability. This approach is based on user's relevance feedback that makes user supervision an obligatory requirement. The research work in [16] presented a generalized SVM as a learning machines kernel for region-based image retrieval. The research work in [17] proposed a salient detector to detect salient regions and ignore other regions. The research work in [18] analyzed the effect of segmentation on retrieval performance of a CBIR system and using a region matching method that integrates properties of all the regions in the images.

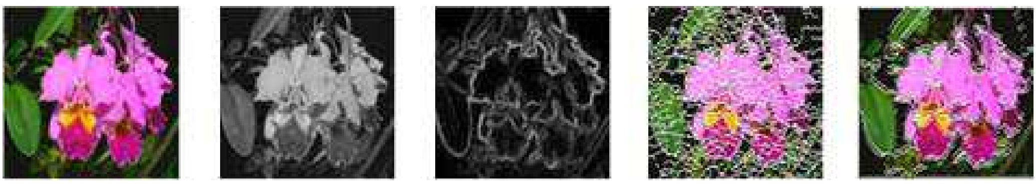
This paper proposes a strategy that does not require any supervision from the user apart from selecting an example image to be used as a query, mark relevant or irrelevant in result set and permit a many-to-many region matching improving the robustness of the system and combine features that expresses meaningful distributions. It is a region-based approach that takes advantage of the robustness of each subsequent module. More specifically, it is based on a watershed segmentation module that produces meaningful regions, and features extraction that combines color, texture and edge density features. The weight of region reflects human perspective, finally based on the feedback. The system updates the weight of individual feature and retrieves a new set.

IV. IMAGE SEGMENTATION

The goal of image segmentation is to partition an image into a set of regions. Different methods for image segmentation have been applied to region-based tasks for different goals, e.g., image retrieval, image annotation, and object recognition. The most intuitive method for image segmentation is to segment objects from an image for region-based image matching even though this is very difficult. However, the segmentation results greatly affect the performances of region-based tasks.

In this paper, the watershed segmentation [7], which is an efficient, automatic, and unsupervised segmentation method for gray-level images, is used to partition an image into non overlapping regions. First, the preprocessing of gradient calculation is essential. Only in the gradient image, the boundaries of objects could be located on the ridges and taken as watershed pixels, as shown in Fig 2.c. and then the watershed algorithm could work in the right way as in Fig 2.d.

Because the basic watershed algorithm is highly sensitive to gradient noise, it usually results in over-segmentation. To overcome this problem, region merging algorithm is applied as a post-processing stage [8], as illustrated in Fig 2.e. Regions are merged until the output meets a given criteria which can be the number of regions or a dissimilarity value between homogeneous regions. Fig. 2 shows steps of watershed algorithm.



(a) (b) (c) (d) (e)

(a) Original Image - (b) Grey Image - (c) Gradient Image
(d) After Watershed - (e) Merged Regions

Figure 2. Watershed steps

V. REGION FEATURE EXTRACTION

Two properties are used to describe a region; the visual features extracted from the region and its importance.

A. Region Visual Feature Extraction

In the current implementation, each region of an image is characterized based on its extracted color, texture and shape features. In image retrieval systems, color is the most commonly used feature. The main reason is that it is independent of image size and orientation. Also, it is one of the most straight-forward features utilized by humans for visual recognition and discrimination. In this paper, the HSV (hue, saturation, value) color space [2] is used. HSV is the most preferred color space by artist because of its similarities to the way human tends to preserve information about color. Considering the color information, the mean μ and the standard deviation σ, from each channel of the HSV (hue, saturation, and value) color space are extracted in this proposed system.

Texture is the visual patterns that have properties of homogeneity that do not result from the presence of only a single color or intensity. In this work, Gabor filters [3] are applied on the image with different orientation at different scale, and the mean μ and standard deviation σ are extracted. Five scales and six orientations are used in this implementation.

Because the edge direction histogram has the characteristics of shift invariance and scale invariance, it is used to describe the shape information [4]. In brief, first, the Sobel operator is used for edge detection for five categories: vertical, horizontal, 45° diagonal, 135° diagonal, and isotropic (non edge). Second, edge density is obtained for each category and for each region in image by the following equation.

$$f = \frac{1}{A} \sum_{p \in R} e(p) \tag{1}$$

Where e is any edge from five categories, R is region, p is every pixel in region R, and A is area of the image.

B. Region Importance Decision

In this research work, two assumptions are involved in evaluating the region importance decision (region-weighting scheme) and then establishing the image similarity measure, because not all regions are with the same importance [12]. First, importance assigned to the region whose pixels are closer to the center. Region assigns higher weights to the pixels near the attention center and lower weights to the pixels which are more remote. Second in this research work, importance is assigned to the region attended to occupy large area. Higher weights are assigned to the region that has large area and lower weights to the region that has small area.

According to user's visual perception, each region is assigned to a weight of importance, which is inversely proportional to the distance between the pixels of the region and the attention center. The Gaussian model of the distance between the pixel and the attention center used to evaluate the importance PI_i can be defined as:

$$PI_i = \exp\left(- \frac{dis(i, c_0)}{\sigma}\right) \tag{2}$$

where, dis is the Euclidean distance of the location difference between pixel i and the attention center c_0, and σ is the standard deviation of all distances between each pixel in the entire image and the attention center. By considering the region sizes, the region weighting importance w_i is given by the sum of the importance of the individual pixels inside region R, i.e.

$$w_i = \sum_{j \in R_i} PI_j \tag{3}$$

The sum of the total region weighting importance of each image should be normalized to 1. That is, the constraint of the region weighting importance is as follows:

$$\sum_{i=1}^{m} w_i = 1 \tag{4}$$

where, m is the total number of regions in the image.

According to user's visual perception, each region is assigned to an importance weight, which is proportional to region attending to occupy large areas. Each region weight is number of pixels in this region divided by the total number of pixels in all regions

$$w_j = \frac{\text{No.of pixel in region}}{W^*h} \quad (5)$$

Where w_j weight of region j ; W,h dimension of image

VI. IMAGE SIMILARITY MEASURE

Since the image segmentation may not be perfect, the integrated region matching (IRM) [6] algorithm allows one region of an image to be matched to several regions of another image. IRM is more robust to inaccurate image segmentations, as shown in Fig. 3.

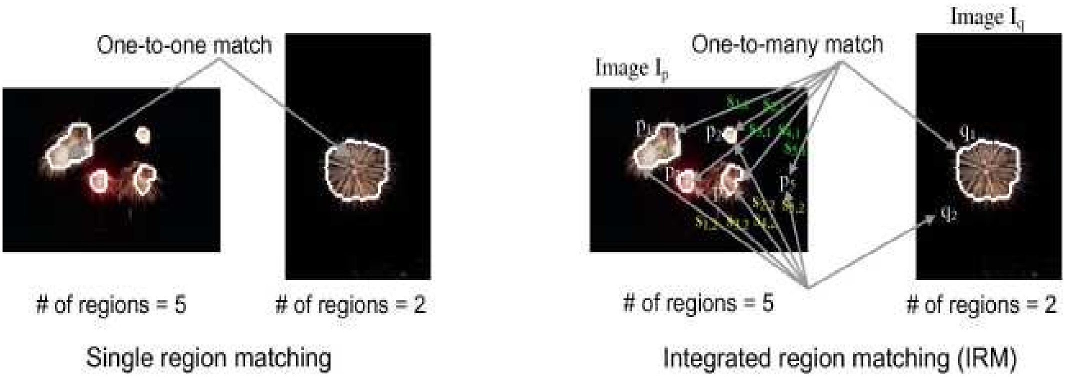


Figure 3. Robustness of integrated region matching (IRM) to inaccurate image segmentation.

Assume that an image I_P contains m regions and an image I_Q contains n regions. A matching between regions p_i and q_j is assigned a significance credit $s_{i,j}$, where this credit represents the importance of the matching in determining the similarity between the two images. Furthermore, let $d(p_i, q_j)$, i.e. the region feature distance between p_i and q_j, be the Euclidean distance. The IRM distance between I_P and I_Q is given by the weighted sum of all the similarities between the region pairs, i.e.

$$d(I_P, I_Q) = \sum_{i=1}^{m} \sum_{j=1}^{n} s_{i,j} d(p_i, q_j) \quad (6)$$

The IRM algorithm attempts to fulfill the significance credits of regions by assigning more significance with respect to how possible will be the minimum distance between regions. Initially, assuming that $d_{i',j'}$ is the minimum distance, we set $s_{i',j'} = \min(wp_{i'}, wq_{j'})$. If $wp_{i'} \leq wq_{j'}$, then $s_{i',j} = 0$, for j ≠ j' since the link between regions i' and j' has filled the significance of region i'. The significance credit left for region j' is reduced to $wq_{j'} - wp_{i'}$.

The procedure steps of the IRM algorithm are summarized as follows:

1) Let wp_i be the significance of region i in image p and wq_j be the significance of region j in image q. Let si,j be the significance credit of the matching between region i of image p and region j of image q.

2) Set L = {}, denote M= {(i, j) : i = 1, ...,m; j = 1, ..., n}.
3) Choose the minimum di,j for (i, j) ϵ M−L. Label the corresponding (i, j) as (i’,j’).
4) min($wp_{i'}$,$wq_{j'}$) → si’,j’ .
5) If $wp_{i'} \leq wq_{j'}$, set si’,j = 0, j ≠ j’; otherwise, set si,j’ = 0, i ≠ i’.
6) $wp_{i'}$ − min($wp_{i'}$, $wq_{j'}$) →$wp_{i'}$’ .
7) $wp_{j'}$ − min($wp_{i'}$, $wq_{j'}$) → $wp_{j'}$.
8) L + {(i’, j’)} → L.
9) If $\sum_{i=1}^{m} wp_{i'} > 0$ and $\sum_{j=1}^{n} wp_{j'} > 0$ go to Step 3; otherwise, stop.

The values of wp_i and wq_j are chosen to represent the region weighting importance (i.e. significance) of regions p_i and q_j in the images p and q, respectively. Both values are assigned by the method described in section 4.2, in some other systems, uniform schema (all regions with the same importance) and other used area schema.

After calculating similarity for each feature, each feature dimension is normalized to the range [0, 1] in order to prevent a dimension with large value from dominating the others.

$$sim_{pqf} = \frac{sim_{pqf} - min_k}{max_k - min_k} \tag{7}$$

Where max_k and min_k refer to the smallest and largest values in sequence. Our total similarity can be defined as:

$$sim_{pq} = \sum_{f=1}^{F} W_f sim_{pqf} \tag{8}$$

Where F is number of feature, N is number of image, W_f is the weight of each feature.

VII. RELEVANCE FEEDBACK

Relevance feedback is the most popular way to acquire feedback on the retrieved images from users for performance improvement. The strategy is to ask users to mark relevant and/or irrelevant retrieved images after each round of image retrieval. Information collected from the returned images is utilized to further improve retrieval performance in the next round.

There are two types of relevance feedback; long term [9] and short term [10]. Short term relevance feedback is dealing with the current feedback session but ignoring historical data from other users. This potentially results in a great loss of useful information but long term is recording and collecting feedback knowledge from different users over a variety of query sessions. It can be implemented to further improve the performance of content-based image retrieval in terms of effectiveness and efficiency. For this reason, long-term learning has an increasingly important role in multimedia information searching.

Before describing the relevance feedback technique, first formalize how an image object is modeled, assuming that image object is represented as I(F,S,W), where:
F = {f_i} is a set of low level visual features associated with the image object, such as texture, color and shape.

$S = \{s_{i,j}\}$ is a set of similarity measure between query image and each image in the database for every low feature

W = $\{w_i\}$ is the weight of each feature.

Based on this image object and similarity measure described above, the retrieval process is described below:

Initialize the weights to W0, every weight is initially of the same importance.

$$W_i = W0_i = \frac{1}{F} \quad (9)$$

The user interfaces with the system by entering his query image and asking for similar images.

The query image Q, is distributed among different features $f_i$according to their predefined weight W_i and the total similarity is calculated

$$sim_{pq} = \sum_{i=1}^{F} W_i * sim_{pqi} \quad (10)$$

The objects in the database are ordered by their overall similarity to Q. The NMsim are returned to the user, where NMsim is the images with highest similarity

For each one of the retrieved objects, the user marks it as relevant or irrelevant according to his information and perception subjectivity.

The system updates the weights (described below) according to the user's feedback. Then, the system adjusts Q and starts new query.

The system updates weights according to user relevance feedback as follows: let $Msim$ be the set of most similar N_{Msim} according to the overall similarity sim and $Fsimi$ is the set of most similar according to feature j.

To calculate the weight for each feature, first initialize Wti= 0 and then use the following procedure for each feature in:

$$\begin{aligned} W_{ti} &= W_{ti} + score \qquad \text{if } Msim \text{ is in } Fsimi \\ &= W_{ti} + 0 \qquad \text{if } Msim \text{ is not in } Fsimi \end{aligned} \quad (11)$$

Where score= $Rscore$ if Relevant and score= $IRscore$ if irrelevant.

After this procedure, if Wti <0 set it to 0. Let WT=$\sum Wti$ be the total weights. The weights are then normalized by the total weight to make the sum of the normalized weight equal to 1.

$$W_{ti} = \frac{Wti}{WT} \quad (12)$$

This research integrates long term feedback with short term feedback, uses short term by high learning factor to accelerate learning for this user, and uses long term feed back by small learning factor to avoid spam.

$$Wnewi = (1-\eta)\ Woldi + \eta\ (Wti) \quad (13)$$

where $0 \le \eta \le 1$.

VIII. EXPERIMENTAL RESULTS

To evaluate the retrieval performance of the proposed system, this study used a CIRES[11] (Content Based Image Retrieval System Help) image database containing 900 images from 9 different categories. Each category contained 100 images. The selected categories are: Birds, Flowers, Texture, Bridge and Building, Landscapes, Transport, Bugs, and Mammals with 128*128 pixel resolutions.

In order to obtain an objective evaluation of the different retrieval techniques, the categories to evaluate the retrieval performance are used in our experiments. But practically, the system enables the user to select the images that are meaningful, while not being subjected to categorization.

A retrieved image was considered as relevant if it belonged to the same category as the query image. The retrieval accuracy was computed as the average precision rate of 54 queries (six queries for each category) from the top N retrieved image. The precision rate for each query is defined as R/N, where R is the total number of relevant images and N is the total number of retrieved images.

A. Example of Image Databases

Figure 4 contains an example of datasets which indicates the diverse contents of the dataset.

Figure 4. Example of dataset

B. Evaluation of Region-Based Image Retrieval:

Region based image retrieval is compared to the classic content based image retrieval, as shown in Fig. 5. To ensure objective comparison, the same features were used with relevance feedback and with proposed weight schema for both retrieval methods.

From Fig. 5, it can be notified that our proposed region based image retrieval has higher precision values for each top N than the classic content based.

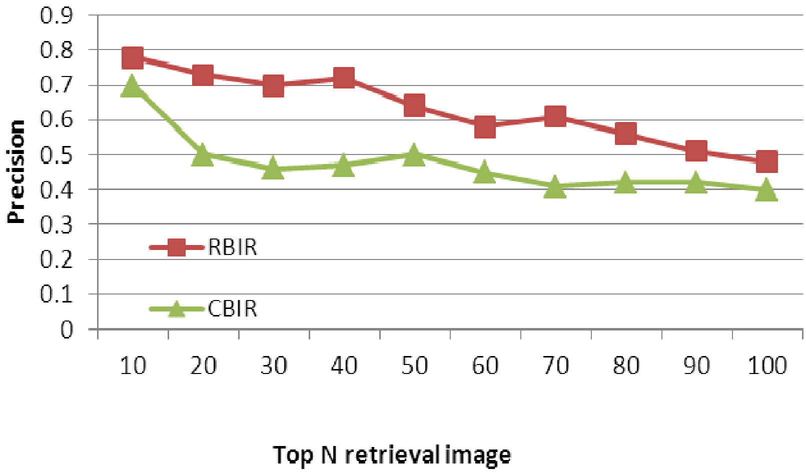


Figure 5. Comparison between region based image retrieval with content based image retrieval.

C. Evaluation of Proposed Weight Schema

Proposed weight schema is compared to area percentage schema and uniform schema is shown in Fig 6.

Figure 6 illustrates how each schema reflects the user perception. Uniform schema gives lowest precision because regions do not have the same importance for humans. Area schema is better than uniform because the attention of humans goes to the region occupying large area. Proposed weight schema is slightly better at most Top N because it combines attention of area with region in center.

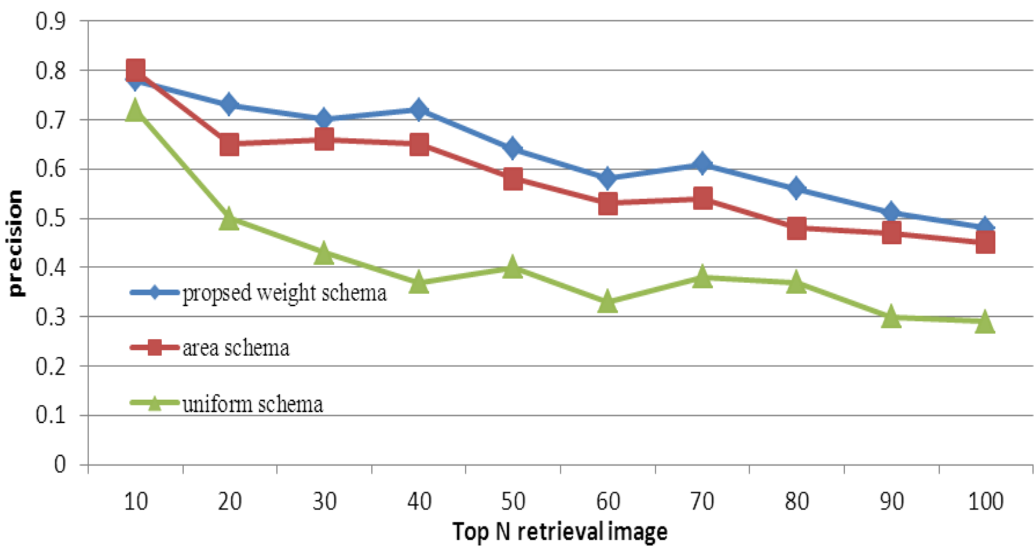


Figure 6. Comparison between area schema, uniform schema, and proposed weight schema

D. Iterative Feedback

One of the issues to improve CBIR is relevance feedback. Relevance feedback improves the results to the next round.

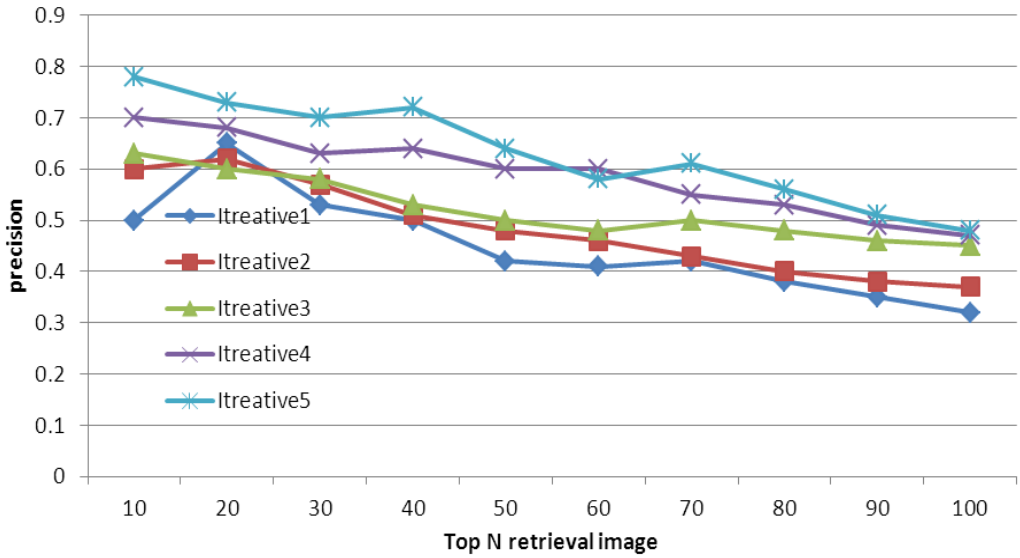


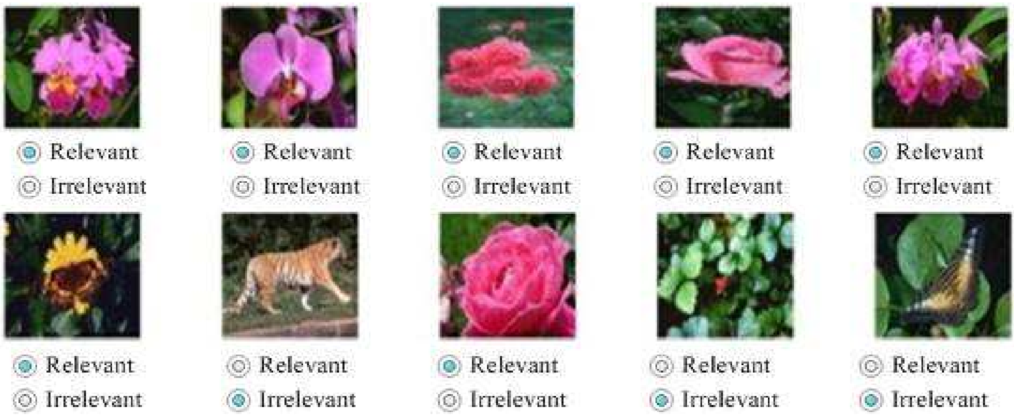
Fig. 7 results change from round to another starting from the default values (iteration 1) till finding the most

E. Examples of using the Proposed Retrieval System

Figure 8 shows the number of iterations for the relevance feedback (user selects if image relevant or not), each round increases rate of the performance.

(a)

(b)



(c)

(d)

(a) First round (b) Second round (c) Third round (d) Fourth round

Figure 8. Iterative feedback for ten retrieval images.System improves itself after each iteration because it takes user vision.

IX. CONCLUSION

With the rapid development of computer vision technologies, image retrieval applications become an emerging field on the Web where various kinds of services are provided for Internet user. In this study, the major contribution is its integration of RBIR with the relevance feedback algorithm. An efficient and unsupervised segmentation is used. Several features are extracted from regions; the color, texture, and edge density features. Multiple regions matching scheme is used to reduce the influence of inaccurate segmentation. A region-weighting scheme reflecting the process of human visual perception is proposed to enhance the weighting importance assigned to region by integrating spatial location and size weighting method.

Relevance feedback algorithm was used by the weight of the feature that improves retrieving of the relevant images. The importance of the feature that hinders this process is reduced. Additionally it combines short term and long term to accelerate learning technique for user but avoid spamming. For future work, it is intended to exploit such an approach that can further improve retrieval accuracy.

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البحث عن الصور عن طريق محتوياتها وتقسيمها الى مناطق ويمساعدة ردود مستخدمي محرك البحث

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أستاذ بقسم الإتصالات والإلكترونيات والحاسبات – كلية الهندسة – جامعة حلوان

إن البحث خلال الصور بتقسيمها لمناطق – وهو إحدى طرق البحث عن الصور بإستخدام محتوياتها – هو نقطة بحثية مهمة. تعرض هذه الورقة البحثية كيفية ربط البحث عن الصور من خلال مناطقها مع ردود مستخدمي محرك البحث وذلك لتعزيز أداء طرق البحث عن الصور بإستخدام محتوياتها. تم إستخدام تقنية المياة المجمعة لإستخلاص كل المناطق داخل الصورة. لكن، ليست كل المناطق بنفس الأهمية. لذلك ، تم عمل معيار رقمي للمناطق يحاكي الإدراك البصري للإنسان وتقييمه لأهمية هذه المناطق بالنسبة للصورة المراد البحث عنها. بالإضافة إلى أن استخدام ردود فعل مستخدمي محرك البحث وعمل مطابقة بينها وبين المعيار الرقمي لمناطق الصور سوف يحسن عملية إسترجاع الصور تدريجياً، وذلك التحسن التدريجي سوف يحسن نتائج البحث عن الصور من خلال ردود فعل المستخدمين.