ISFR: AN EFFECTIVE FRAMEWORK FOR EFFICIENT IMAGE RETRIEVAL SYSTEM BASED ON INTERACTIVE SEGMENTATION AND FUZZY RULES

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ABSTRACT

In an image retrieval system, the major challenges are image understanding and image annotation. This paper presents an Interactive Segmentation and Fuzzy Rules (ISFR) framework that includes two major components: Interactive Image Segmentation (IIS) for image understanding and Fuzzy Annotation Theory (FAT) for image annotation. IIS extracts multiple objects and background regions from the images and identifies the user context objects in the images through multiple markers. FAT is used to develop the image annotation systems. The colour, shape, and texture of objects are used to represent the visual concepts of the images. This paper extends and enriches the fuzzy based knowledge representation to map visual concepts to high level concepts. Thus the formal specifications of the visual concepts to the corresponding high level concepts are constructed. The proposed ISFR framework produces automatic annotation of segmented objects and retrieves images that best match user's expectations. Experiments on benchmark dataset validated that the proposed ISFR framework yields better segmentation than the existing algorithms.

Keywords: interactive segmentation, fuzzy rules, annotation, high level concept, image understanding, knowledge extraction.

INTRODUCTION

In recent years, a large amount of digital images are available on the Internet. It becomes difficult to retrieve images unless they are well organized. Current commercial image retrieval software systems use text based search techniques and work using the keywords embedded in the image link or tag. Hence the retrieved image set is visually contaminated with irrelevant images. This problem is solved by annotation based image retrieval.

Annotation stands for the process of describing images and retrieval stands for the process of finding images. Retrieval of images using query by example is computationally expensive and time consuming due to excessive feature extraction. This problem can be solved by applying keyword filter in the query by example to remove semantically dissimilar images from the result. Hence the objective of the proposed scheme is to retrieve the images based on automatic annotation that uses low level features and high level concepts that reduce the semantic gap between the desired images and the available images. Several advanced image annotation schemes based on machine learning approaches have been proposed in [23] [24] [26] [27].

Annotation of many images depends on semantic understanding of visual context. The semantic understanding of an image can be achieved by various segmentation algorithms. Image segmentation helps to separate the desired object from the background. Some of the segmentation algorithms are extraordinarily successful and have become popular in many applications and products. A rich amount of survey on image segmentation has been published over the years. Published work in image segmentation includes areas like object understanding, region growing, region merging, splitting and so on. Automatic image segmentation is a difficult problem which requires modeling the problem based on domain knowledge. Also some form of human intervention is required to correctly segment the object from the images. Moreover, automatic segmentation methods are not generic. Interactive image segmentation schemes that are easy to understand and inexpensive to implement have received a lot of attention over the years.
The current variations on interactive segmentation algorithms are mostly built on top of a small set of core algorithms like graph cuts, random walker and shortest paths. All the three algorithms have been used in a common framework that allows them to be seen as instances of a more general seeded segmentation algorithm [13]. In [19], semi-automatic segmentation method handles objects which are composed of different similar areas. The primary focus of this work is not only on the accuracy of segmentation and recognition, but also on the efficiency of the algorithm. Both accuracy and segmentation play important roles when dealing with image annotation. Image annotation has the major problem of predicting correct labels corresponding to objects or background in images. The main method for automatic image annotation is to automatically learn semantic concept models for image patches and use these concept models to label new images. One common problem in annotation is that each image is associated with a number of semantic keywords which poses the multi-label problem. For example, an image may have only five objects but the number of associated tags with the image may be around fifty [15].

A supervised image annotation process is proposed in [21]. This process extracts colour and texture properties for inter and intra-image analysis, individually. Salient features are combined with symbolic descriptions for semi-automatic and incremental annotation of images. The result is a group of labels relating to the image content. However, manual annotation is not scalable and hence expensive when the volume of data increases. Moreover the manually annotated images are not accessible for average users unless they are well organised.

In the proposed work, an Interactive Image Segmentation (IIS) is introduced where the user can specify the object and background in the images conceptually using markers that can be drawn as lines or curves. IIS uses two colour markers namely green and blue. The green colour represents the objects in the image and the blue colour specifies the background. After marking, the regions that have pixels inside the object markers are called object marker regions, while the regions that have pixels inside the background markers are called background marker regions.

After estimating the colour value in the marker specified region, a comparison is made on the neighbourhood regions in that image. If two regions have the same colour, merge these two regions into a single region. If the colour differs then comparison is made with other neighbourhood regions in the image. This segmentation is iterated till the image is divided into two regions: object regions and background regions. After objects are extracted from the images, these objects are annotated by the Fuzzy Annotation Theory (FAT). Unlike other fuzzy annotation techniques, our work uses knowledge based fuzzy rules for annotating images based on predefined thirteen category classes. At first the visual features like shape, colour, and texture of each object in the images are extracted. These features are used as input for generating fuzzy member functions. Then FAT is used to annotate the segmented objects. After annotating the segmented objects, the fusion model is used for propagating the annotated label for images. Finally the images are retrieved based on the dominance of the objects in the images. The critical issue of mapping the visual concepts to high level human concepts is addressed by our ISFR framework by including two subsystems namely Image Interactive Segmentation (IIS) and Fuzzy Annotation Theory (FAT).

RELATED WORK

Image segmentation

Segmenting an image into semantically meaningful parts is a major task in human vision. Automatic methods are able to segment an image into coherent regions, but such regions generally do not correspond to complete meaningful parts. The disadvantages of segmentation by selecting patch-based representatives are discussed in [21].

In automatic segmentation, the user selects the initial seed selection method and then region growing algorithm is applied. However, it can't detect the correct region in the image. In this method, the seed selection varies with respect to the user view [8]. Semantic segmentation has been done by designing region-based object detectors. Such an approach can be divided into several sub-problems. Initially ground truth algorithm is applied and then expected object and background are separated from the image [16].In this method the term 'object' is relative and it can vary from user to user.

The authors present an automatic seeded region growing algorithm for colour image segmentation in [6]. First, the input Red-Green-Blue (RGB) colour image is transformed into YCb Cr colour space [6]. Second, the initial seeds are automatically selected. Third, the colour image is segmented into regions where each region corresponds to a seed. Finally, region-merging is used to merge similar or small regions. In this method the author use RGB colour feature method and they do not concentrate on other features. Another framework to generate and rank plausible hypotheses for the spatial extent of objects in images using bottom-up computational processes and mid-level selection cues has been proposed in [10]. This method needs some training data for segmenting the images.

In [17], the authors address the problem of segmenting an image into regions based on a predicate for measuring the evidence for a boundary between two regions using a graph-based representation of the image. The algorithm runs in time that is nearly linear to the number of graph edges and hence the algorithm takes more time for execution. Hence their algorithm suffers the scalability problem with large-scale annotation of web images. Their approach is based on the concept of visual synset, which is a collection of images that are visually-similar and semantically-related. Few works are based on manual annotation [12]. Several methods have been proposed in the past for image auto-annotation which tries to model image-to-image, image-to-label and label-to-label similarities. This method comes under the category of the supervised annotation models that work with large annotation vocabularies. This method is not suitable for databases of large volume.

Even though few attempts have been made to achieve automatic segmentation, they suffer from limitations. The term 'object' is user dependent and the generalization of this term is very difficult. They deal with specific colour models and they don't follow a generalized approach. Some of them need training data which is difficult to get in the real world applications. Few works avoid these problems; however they have the scalability problem. In this proposed work, interactive segmentation is used for object detection in images .This interactive segmentation algorithm accurately detects the user interested objects in the images. Hence the proposed work is able to improve the retrieval rate of desired images.

Annotation

Automatic image annotation proposed in [4] refers the visual databases only for the shape related information. The scheme extracts the regions from the image and annotates the image by considering only the shape features. Imagination (IMAGe (semI-) automatic anNotATION) refers to the graph-based link analysis techniques in the development of an effective semi-automatic image captioning system [8]. In their approach, each image is characterized asa set of regions from which

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low-level features are extracted. In this method, they need some training data for annotating unknown images.

In multi-instance learning framework [4], objects are divided into multiple regions. It is difficult to get the semantic concepts of the objects present in the images. The solution for large-scale annotation of web images is based on the concept of visual synset, which is an organization of images that are visually-similar and semantically-related [3].

Automatic image annotation aims at predicting a set of textual labels for an image that describe its semantics. These are usually taken from an annotation vocabulary of few hundred labels. Because of the large vocabulary, there is a high variance in the number of images corresponding to different labels. The annotation proposed in [22] was done based on texture feature and multiple meaning for same images. As a result, the annotation contains more noisy tags. An innovative image annotation tool for classifying image regions in one of seven classes - sky, skin, vegetation, snow, water, ground, and buildings - or as unknown has been proposed in [2].The method in this work uses texture feature only and also it applies seven limited number of visual bag of words [2].

A classifier has been proposed to divide an image into small sized cells for the purpose of annotation [14]. In this classification method, the authors use shape feature to annotate the images. This method is not effective since this needs some training data for annotating unknown images. This classifier uses shape feature alone [14].

The major problem with the existing annotation schemes is that they deal with a single feature of the image. Moreover they have problem in dealing with unknown images. Few works have problems in dealing with large vocabulary and large sized image databases. Hence in this work, texture, shape and colour features are used for annotating images. Experimental results of this work prove that the system provides effective annotation and deals with unknown images in a better way.

PROPOSED WORK

The efficient image retrieval system proposed in this paper has three phases as shown in Figure-1.Interactive Image Segmentation (IIS) phase consists of segmenting image objects through multiple markers based on user interest. After the segmentation of objects, Fuzzy based Annotation Technique (FAT) is applied to segmented objects to annotate the images so that the annotations associated with the images make the retrieval process effective. In the retrieval phase, the dominance of image objects is used to retrieve the images from the image database.

INTERACTIVE SEGMENTATION FOR IMAGE UNDERSTANDING

We propose an interactive segmentation algorithm, which aims to understand the multiple objects in the images through the user interest. In order to emphasize that this approach is able to detect objects in the image based on the interest of different users, we examine the edge based image segmentation algorithm with region merging process which is not able to work like the proposed scheme.

An image does not have well defined edges due to the application of over-segmentation. Hence the first step in the image understanding is to segment an image based on the edges. This helps us to achieve clear edges for region merging. Second step is to apply marker based region merging for concept object identification.

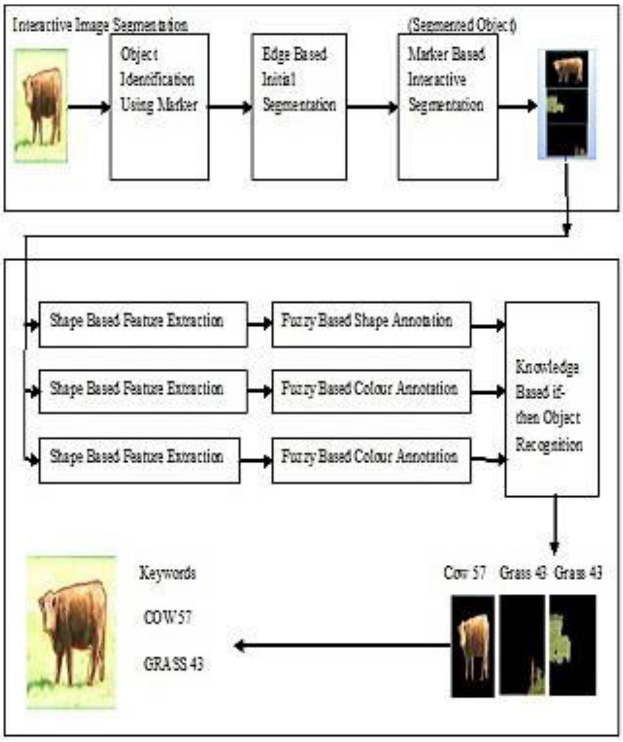

Figure-1. ISFR frame work.

Edge based segmentation with region merging

In our method, we apply mean shift algorithm [18] for initial segmentation to divide the images into a number of regions. There is a need for finding the relation between regions for getting the correct boundary for region merging. So, we apply edge detection [25] process to get boundary between two regions. In every region, the homogeneities of pixel are calculated and it varies from 0 to 1. If f(x, y) is the intensity of pixel value represented from $f^r(x,y) - f^l(x,y)$ then the boundary region may vary among the following forms

1. If $f^r(x_0, y_0) > 0$ and $f^l(x_0, y_0) \geq 0$

No change in the boundary level

2 .If $f^r(x_0, y_0).\ f^l(x_0, y_0) < 0$

Merge right and left region and form a new region

3 If $f^r(x_0, y_0) \leq 0$ and $f^l(x_0, y_0) < 0$

Discard

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After calculating boundary regions from edge based segmentation, the system introduces marker based image segmentation. In this process, user can specify the object and background in image by using interactive marker method. The marker can be drawn as a line or as a curve.

The marker may be a line as follows.

Line= $\sum_{n=0}^{n-1} x+n, y$

The marker may be curve as follows.

Curve=$\sum_{n=0}^{n-1} x+n, y+n$

After drawing the marker in the image, we calculate the similarity of a region to its neighbourhood. The value of colour in the space created by the marker varies typically between zero and one. However, the colour space value is usually scaled by 255 for an 8-bit representation. Each colour can be broken down into its relative intensity in the three primaries corresponding to the spectral response of one of the three types of cones present in the human eye: red, green and blue. The similarity of colour for every region is calculated as follows.

$$R = R_r + R_g + R_b$$

Colour region based segmentation algorithm

Let $R_1 + R_2 + R_3 + \cdots \ldots . + R_n$ denote the number of the regions in the image. The mean of all regions in R_n in terms of R, G and B components is denoted as R_r, R_g and R_b respectively. Our segmentation algorithm is described below.

1. Perform user marker selection.
2. Calculate R, G, andB values for user selected region.
3. Calculate the similarity between adjacent regions using equation (1) for every neighbourhood region that has been marked.
4. Perform region merging.

$$S = (R1_r - R2_r) + \left(R1_g R2_g\right) + (R1_b - R2_b) \quad (1)$$

-

where $R_1$and R_2 denote region$_1$ andregion$_2$ respectively. The merging process for regions is as follows:

$$region = \begin{cases} S = 0 & R1\ andR2\ merge \\ S \neq 0 & R1\ andR2\ same \end{cases}$$

The region $S$with similarity value is extracted. If several regions have the same similarity value, we choose the region corresponding to the neighbouring region having the similar value. If S has the same similarity value to several neighbouring region, we merge those regions then the new regions are obtained. Finally the merged regions are stored into local database and use the merged region for annotation technique.

FUZZY BASED ANNOTATION

The images are considered as a representation of multiple objects. It is very difficult to find suitable keywords for describing images. So we propose the knowledge based fuzzy annotation scheme based on the features of the objects in the image. Many works have been done in knowledge based annotation theory. But the advantage of our approach is that fuzzified image features are used for annotation. The main task carried out in the proposed work is image annotation based on fuzzifying shape, colour and texture features of objects present in the images. These objects are annotated with keywords present in categorized classes. It is a semi-automatic annotation of image content. The procedure for annotation is as follows.

1) Detection of interest object by interactive segmentation algorithm
2) Extraction of feature pattern for each object in the segmented images
3) Fuzzy based knowledge representation for objects
4) Annotation of images

Texture feature extraction

The derivation of our gray scale and rotation invariant texture operator is based on the definition of texture T in a local nxn neighbourhood of a monochrome texture image as the joint distribution of the gray levels [20] of the nine image pixels.

$$T = p(p_0, p_1, p_2, \ldots \ldots, p_n)$$
$$T = p(p_0, p_1 - p_0, p_2 - p_0, \ldots \ldots, p_n - p_0$$
$$T \cong p(p_0)p(p_1 - p_0, p_2 - p_0, \ldots, p_n - p_0$$
$$T \cong p(p_1 - p_0, p_2 - p_0, \ldots \ldots \ldots \ldots \ldots . p_n - p_0)$$

where $p(p_0)$ is the factor that does not provide useful information. Signed differences $p_1 - p_0$ are not affected by the changes in themean luminance; hence the joint difference distribution is invariant against gray scale shifts.

$$T \cong p(s(p_1 - p_0), s(p_2 p_0), \ldots s(p_n - p_0)$$

$$\mathrm{Texture}_{n*n} = \sum_{i=1}^{n} s(p_i - p_0) 2^{i-1}$$

Shape feature extraction

Let I∈ R^3 be a regular surface and S_p be a tangent vector at a point $p \in I$ with $\|s_p\|$=1

The normal curvature [7] of I in the direction of S_p is defined as

$$k(S_P) = f(S_P).S_P$$

where $f(S_P)$ is the shape operator. The maximum and minimum bending of I at p are measured by the two principal curvatures, k1 and K2 $(k_1 \geq k_2)$ that correspond to the maximum and minimum values of the normal curvature k (S_P), respectively. The relation between the principal curvatures and the two classical shape measures by name the Gaussian curvature K and mean curvature H, is given as

$$k_1 = H + \sqrt{H^2 - k}$$
$$k_2 = H - \sqrt{H^2 - k}$$

A point p is represented by a single-value and an angular measure called the shape index $S_I(p)$ which is shown in equation (2)

$$S_I(p) = \frac{2}{\pi}\arctan\frac{k_1 + k_2}{k_2 - k_1} \quad (2)$$

Colour feature extraction

Colour feature is extracted by colour histogram and colour descriptor. The colour histogram specifies the colour pixel distribution in an image. Colour histogram uses two types of colour space that are RGB and Hue Saturation Value (HSV). Colour Histogram (CH) contains occurrences of each colour obtained by counting all image pixels having that colour. Each pixel is associated to a specific histogram bin only on the basis of its own colour. The pixel is not associated to the histogram bin either on the colour similarity across different bins or colour dissimilarity in the same bin. Since any pixel in the image can be described by three components in a certain colour space (red, green and blue), a histogram, i.e., the distribution of the number of pixels for each quantized bin, can be defined for each component.

FUZZY BASED KNOWLEDGE REPRESENTATION

In our approach, a knowledge representation scheme based on Fuzzy Annotation Theory is used for image auto-annotation. This model is based on the number of objects in the image.
FAT is defined as seven tuples.

$$FAT = \{DI, DO, OF, CC, In, Out, IA\}$$
$$DI = \{I_1, I_{2,\ldots\ldots}, I_n\} n \in N \ is\ a\ set\ of\ image$$
$$DO = \{0_1, 0_2, \ldots \ldots 0_m\} m \in Misthesetofobject$$
$$OF = \{OF_1, OF_2, \ldots \ldots OF_p\} wherep \in Pisthesetofobjectfeatures$$
$$CC = \{CC_1, CC_2, \ldots \ldots CC_q\} whereq \in Qisthesetofcategeryclasses$$
$$In = OF \to DO^{\infty} whereInistheinputfunction$$
$$Out = OF \to DO^{\infty} whereOutistheoutputfunction$$
$$IA = DO \to DO(CC) whereIAistheimageannotation$$

Based on FAT, we write fuzzy rules for efficient annotation of images. The general rule for image annotation is given in equation (3).

$$generalrule = \{cc, R_{cst}\} \quad (3)$$

$$whereR_{cst} = f_c X f_s X f_t \to \{0,1\}$$

Here the cc is the category class for R_{cst}, where R_{cst} is the relationship between the shape, colour and texture features. But in general cases, the relationship among the features is either 0 or 1. For example, the feature set for $\{S_1, C_1, T_1\} \to Tiger\ or\ Not$ is very difficult to describe using crisp keyword based annotation. Hence we go for fuzzy rule from FAT.

$$Fuzzyrule = \{cc, F(R_{cst})\} \quad (4)$$

$$whereF(R_{cst}) = f_c X f_s X f_t \to \{0,1\}$$

From equation (4), the cc is assigned to image object based on fuzzy relationship among the features. In fuzzy rules, the relationship among the features depends on the membership function of each feature. The membership function should be in the interval between zero and one. Now the membership function for the concept category cc is $\mu_{cc} = V \to \{0,1\}$.The fuzzy annotation of images depends on F_{AI} which is given in equation (5).

$$F_{AI} = \cup_{i=1,j=1}^{i=m,j=q} DO_i\, CC_j \quad (5)$$

The feature membership functions for colour, shape and texture features are $\mu_c, \mu_s, and\ \mu_t$ respectively. The colour features are the most widely accepted visual descriptors for identification of any object. In this work we use thirteen basic colours for correctly annotating the object. They are black, blue, brown, gold, green, orange, pink, purple, red, white, yellow, violet and indigo. These are called colour prototype classes PC_c for colour based annotation and tags are assigned according to colour features of detected objects in the image. The colour annotation is done by using the RGB values of the detected object with the colour annotated values in the colour space. Suppose more than one colour tags are assigned to the same object, then we neglect the colour annotation and annotate the object using shape and texture features. The distance between the colour features CF_m and colour prototype PC_c is $||CF_m - PC_c||$ and the membership function of colour features of detected objects is based on Gaussian membership function as shown in equation (6).

$$\mu_c = e^{\frac{-||CF_m - PC_c||}{\beta}} \quad (6)$$

where β is a distance threshold. The colour membership function effectively annotates the colour tag for image annotation.

The shape features are able to describe any objects easily. The shape features are also used for retrieving images in the retrieval system. Here we use five basic shapes for correctly categorizing the classes. They are round, rectangle, triangle, diamond and heart. These are called shape prototype classes PC_s for shape based annotation and tags are assigned according to the shape features of detected objects in the images. If the shape features of objects belong to many different shape prototype classes, then we neglect the shape annotation and annotate the object using colour and texture features. The distance between the shape features SF_m and colour prototype PC_s is $||SF_m - PC_s||$ and the membership function of shape features of detected objects is based on Gaussian membership function as follows in equation (7).

$$\mu_s = e^{\frac{-||SF_m - PC_s|\,|}{\beta}} \quad (7)$$

where β is a distance threshold. The shape membership function effectively annotates the shape tag for image annotation.

Finally we annotate the object based on the texture features. The texture features are able to describe any object easily. The shape features are also used for retrieving images in the retrieval system. Here we use five basic shapes for correctly categorizing the classes: {round, rectangle, triangle, diamond and heart}.These are called shape prototype classes PC_s for shape based annotation and tags are assigned according to the shape features of detected object in the images. If the shape features of objects belong to many different shape prototype classes, then we neglect the shape annotation and annotate the object using colour and texture features. The distance between the shape features SF_m and colour prototype PC_s is $||SF_m - PC_s||$ and the membership function of shape features of detected objects is based on Gaussian membership function as shown in equation (8).

$$\mu_t = e^{\frac{-||TF_m - PC_t|\,|}{\beta}} \quad (8)$$

where β is a distance threshold. The shape membership function effectively annotates the shape tag for image annotation.

Fuzzy rule generation

The main goal of generating classes from the features of fuzzy rules is to determine the value of the category classes from the various fuzzy membership functions. This section explains the mechanism of making fuzzy rules from the knowledge based fuzzy annotation theory for annotation. It is converted into 25 rules and more than 100 rule conditions.

Using these prototype classes various fuzzy if-then rules are generated. A sample rule is given below: The following sample rule gives clear specification of the various combinations of different prototype classes using the operators AND and OR.

IF color=black AND shape=rectangle AND texture=rock THEN category classes=Road

In this research work, we apply the above procedure on the twenty three various category classes and generate more than 100 rules and set of sample rules.

PERFORMANCE EVALUATION

In this section, both interactive image segmentation and automatic annotation of image retrieval system are assessed. We also evaluate the performance of the system in terms of image search and retrieval which is our ultimate goal. We perform experimentation through the Microsoft Research in Cambridge (MSRC) dataset which contains 420 images. These images have more than 8000 regions and 1000 tags associated with these originally. We refine these original tags by using our proposed method. Every image is segmented into object and background by using interactive segmentation of user specified regions in the image and automatic annotation is applied to the regions using our method. In general, the experimental evaluation is based on two aspects. In the first section evaluation is based on interactive segmentation algorithm, and the following section the evaluation is based on fuzzy automatic annotation and in the final section the system retrieval performance is evaluated based on precision and recall.

Evaluation of interactive segmentation

The proposed method provides pixel level segmentation of the objects in the image. In this segmentation method, training and test data are not used because training data may occupy more memory space. Hence we used interactive segmentation for user specified regions. Interactive segmentation means user can specify the desired object and background in the images. Interactive segmentation is required since the object for an image can vary according to the user interest. For example, in the image shown in Figure-2, the user can select either banana as an object or hand as an object. Hence we use interactive segmentation. User can specify the object and the background in an image by using either green markers or blue markers.

Figure-2. Object varied from user.

After we initialised the marker in the image, we extract the colour feature in that marker specified region of the image as shown in Figure-3. Some of the segmentation results are shown in Figure-4.

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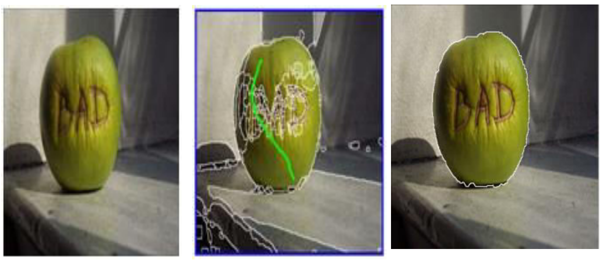
(A) (B) (C)

Figure-3. A. original image. B. object and background applied image. C. segmented result.

After estimating the colour value in that marker specified region, compare that value with the neighbourhood regions in that image. If two pixels in two regions have same colour feature values, merge these two regions into a single region. If not, these two regions are compared with other neighbourhood regions in the image. This segmentation continues till the image is merged into two regions: objects and background region.

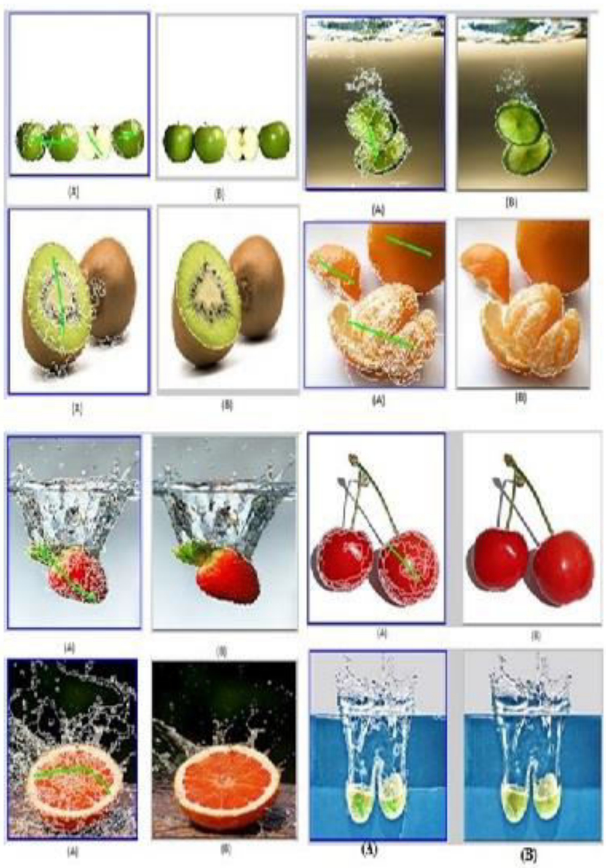

Figure-4. A. Input image, B. segmented image.

In this section we compare our interactive segmentation with Multi-label Manifold Ranking (MSMR) algorithm. To evaluate segmentation we compare True Positive Rate(TPR) and False Positive Rate(FPR) for these segmentation results. It is shown in Table-1.

Evaluation of annotation

The basic aim of this paper is to annotate the images automatically. Automatic Image Annotation (AIA) is one of the promising solutions to address this challenge. The main idea of AIA technique is to automatically learn semantic concept models from image samples, and use these concept models to label new images. In a typical image annotation problem, each picture is usually associated with a number of different semantic keywords. This poses so called Multi-Label Classification problem, in which each image may be associated with more than one class label. So in this fuzzy based automatic annotation method we suggest 23 classes. They are flower, grass, sign, sky, building, tree, water, bird, road, book, chair, cat, dog, boat, body, face, car, mountain, bicycle, cow, horse, sheep and aeroplane.

From Table-1, we observe that the proposed segmentation method gives higher TPR rate and the lower FPR rate when compared to MSMR algorithm based segmentation.

After segmenting objects from the images, the fuzzy rules are applied for image annotation. Thesample fuzzy rules are given below.

$$\forall r \in M, (c_r = NA) \cap (s_r = NA) \cap (742 * 10^{-4} < t_r < 2596 * 10^{-7}) \rightarrow r = c_{flower}$$
$$\forall r \in M, (3237 * 10^{-3} < c_r < 3397 * 10^{-4}) \cap (s_r = NA) \cap (10 < t_r < 20) \rightarrow r = c_{grass}$$
$$\forall r \in M, (34 * 10^{-3} < c_r < 74 * 10^{-4}) \cap (4 < s_r < 16) \cap (4 < t_r < 15) \rightarrow r = c_{sign}$$
$$\forall r \in M, (22 * 10^{-5} < c_r < 41 * 10^{-4}) \cap (2 < s_r < 13) \cap (7 < t_r < 10) \rightarrow r = c_{sky}$$
$$\forall r \in M, (0748 * 10^{-3} < c_r < 3259 * 10^{-3}) \cap (1 < s_r < 5) \cap (8 < t_r < 23) \rightarrow r = c_{building}$$
$$\forall r \in M, (0170 * 10^{-4} < c_r < 125 * 10^{-3}) \cap (7 < s_r < 0) \cap (3 < t_r < 70) \rightarrow r = c_{tree}$$
$$\forall r \in M, (0468 * 10^{-4} < c_r < 1139 * 10^{-3}) \cap (2 < s_r < 25) \cap (7 < t_r < 45) \rightarrow r = c_{water}$$
$$\forall r \in M, (6290 * 10^{-3} < c_r < 9145 * 10^{-3}) \cap (2 < s_r < 56) \cap (9 < t_r < 52) \rightarrow r = c_{bird}$$
$$\forall r \in M, (0328 * 10^{-4} < c_r < 8409 * 10^{-4}) \cap (7 < s_r < 33) \cap (4 < t_r < 68) \rightarrow r = c_{road}$$
$$\forall r \in M, (0347 * 10^{-4} < c_r < 749 * 10^{-3}) \cap (2 < s_r < 19) \cap (15 < t_r < 56) \rightarrow r = c_{book}$$
$$\forall r \in M, (0248 * 10^{-3} < c_r < 187 * 10^{-4}) \cap (13 < s_r < 37) \cap (16 < t_r < 60) \rightarrow r = c_{chair}$$
$$\forall r \in M, (0048 * 10^{-3} < c_r < 173 * 10^{-4}) \cap (13 < s_r < 89) \cap (15 < t_r < 43) \rightarrow r = c_{cow}$$
$$\forall r \in M, (4090 * 10^{-4} < c_r < 775 * 10^{-3}) \cap (3 < s_r < 49) \cap (7 < t_r < 65) \rightarrow r = c_{face}$$

Table-1. The TPR and FPR for different images (MSMR Vs Our approach).

Image	Method	TPR %	FPR%
Sky	MSMR	96.87	00.96
	Our approach	97.98	0.54
Fruit	MSMR	94.23	0.56
	Our approach	96.45	0.43
Cat	MSMR	96.87	0.67
	Our approach	98.23	0.53
Car	MSMR	92.23	0.75
	Our approach	98.27	0.43
Building	MSMR	97.22	0.45
	Our approach	97.45	0.34
Road	MSMR	87.23	1.34
	Our approach	92.45	0.98
flower	MSMR	86.98	0.96
	Our approach	94.56	0.92
House	MSMR	92.67	0.67
	Our approach	93.34	0.42

Figur-5 shows the annotation for the regions based on the rules. After each image region is annotated,

ARPN Journal of Engineering and Applied Sciences

adjacent regions with the same annotation are merged together. Some exemplar tag-to region results are shown in Figure-6. These results over various conditions validate the effectiveness of the proposed solution. The experimental results presented here demonstrate that our framework for image annotation can be applied with sufficient reliability to content-based retrieval in images. After annotating every region, the annotation accuracy for all visual bags of words is shown in Figure-7.

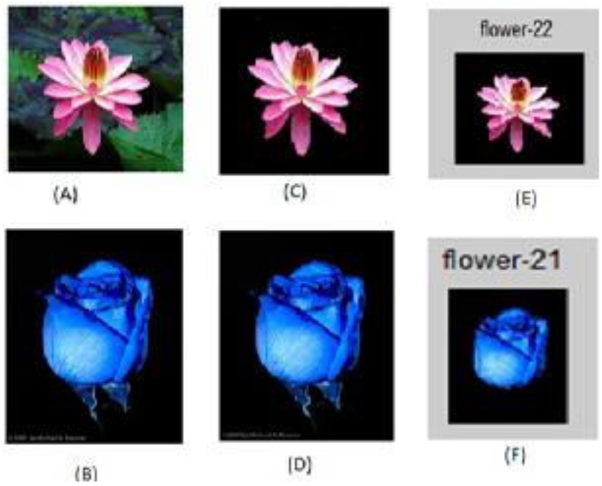

Figure-5. A, B: Original image C, D: Segmented image, E, F: Annotated image.

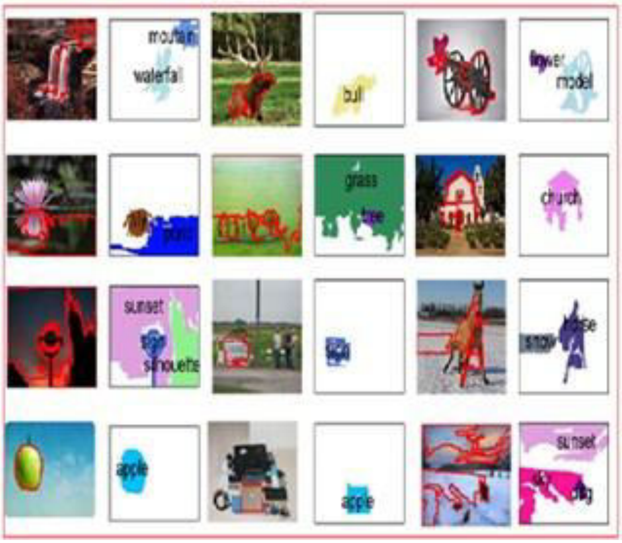

Figure-6. Annotation result.

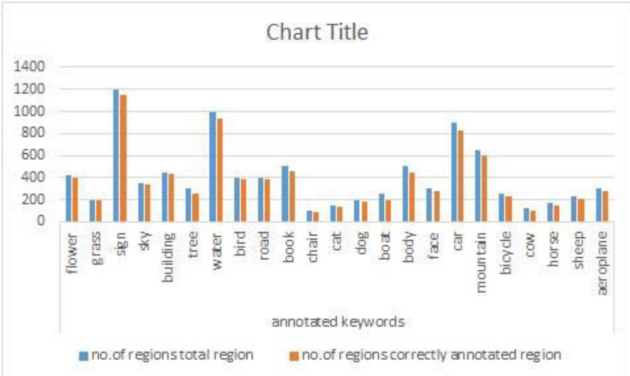

Figure-7. Annotation accuracy.

Total number of regions is 8400 and the number of correctly annotated regions is 7500. The percentage of the correctly annotated images is 89.45%.

Image search and retrieval

In image retrieval, searching a particular image in social media and any other search engine is difficult to retrieve correct images. So the proposed system introduces new type of searching parameter called dominance of the object that helps to retrieve the image based on the object size rather than image size. e.g.20% of image is composed of flowers. The Dominance is explained in equation (9).

$$Dominance = \frac{I_s}{I_B} \tag{9}$$

Where I_s denotes the total number of pixels in the objects of the image and I_B represents the number of background pixels in the image. The proposed dominance based image retrieval system is evaluated based on precision and recall. They are defined as in equation (10) and (11).

$$precision = \frac{|relevant_{iamges}|}{|retrieved_{images}|} \tag{10}$$

$$recall = \frac{|ACC_{correct}|}{|relevant_{images}|} \tag{11}$$

where $relevant_{images}$ represents positive images, that are relevant to the user query at each iteration and $retrieved_{images}$ represents the results returned by the retrieval system. $ACC_{correct}$ is the image set in the user session actually satisfied by the user. The precision is system relevant and the recall is user relevant. The comparison of search and retrieval with and without dominance are given in Table-2.

VOL. 10, NO. 9, MAY 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

Table-2. Precision and Recall for different images Without Dominance Vs with Dominance

Images	Search method	Precision	Recall
flower	Without Dominance With Dominance	96.4 98.7	45.67 55.66
car	Without Dominance With Dominance	87.6 93.67	46.7 67.7
sky	Without Dominance With Dominance	92.45 93.43	45.78 49.6
building	Without Dominance With Dominance	98.23 98.34	45.6 47.23
cat	Without Dominance With Dominance	89.6 92.7	46.89 48.74

CONCLUSIONS

The main contribution of this work is the performance improvement of image retrieval system through the understanding of images. Most of the traditional approaches are based on the annotation schemes which are not able to understand the objects present in the image. Hence the performance of these schemes in image search and retrieval is not up to the mark. However, the method proposed in this paper follows understanding of image objects by employing techniques like interactive image segmentation, annotation of image objects through the shape, colour, and texture based on fuzzy rules and finally retrieving the images based on dominance of objects in the images. The experimental evaluation demonstrates the efficiency of our approach in image retrieval

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