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A New Concept Based Fuzzy Similarity Measure for Image Retrieval Systems

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Abstract: The main goal of image retrieval systems is image categorizations based on their contents. One of the major steps in Content Based Image Retrieval (CBIR) systems is 'similarity measure'. In this paper, a new similarity measure based on the fuzzy monotonic inclusion is represented. At First, an image is segmented to several regions, and then each region is described by a fuzzy set. Finally, extracted features from each region are mapped into a fuzzy similarity model. Thus, for every image region, both properties of fuzzy location and area are extracted. This method has two advantages, first, using two new features, location region and area region; second, creating content based relation among image regions based on Fuzzy Inclusion. The experimental results on Label Me database, a real world image dataset including 163,000 images, show superiority of our proposed method compared with UFM and Fuzzy histogram.

Keywords: Fuzzy similarity; Image retrieval; Monotonic fuzzy inclusion measure; Similarity measure

I. INTRODUCTION

With the increase of the number of digital images, researcher's trend to invent new techniques to extract and classify images based on their contents. Thus, image retrieval techniques have been developed. The main task in the field of image retrieval is the content extraction from every image and the huge contents that are hidden in the features and objects of each image [1]. Thus, image retrieval systems try to make bridge among features and concepts. Generally, image retrieval procedures are divided into three phases; the first phase is feature extraction, the second one is the image segmentation and the third phase is the similarity measure [2]. In the first phase, three main features i.e. color, texture and shape are extracted that are called low level features [2]. In the segmentation phase, the image is divided to several small partitions. In the segmentation process, the image is partitioned into multiple segments such that every segment contains some concepts of the image [3]. Region based segmentation has been a noticeable subject in the field of image retrieval. K-means algorithm is a common technique in the segmentation of an image [4]. In recent years, fuzzy region approaches have received a lot of attention [3,5,6]. Wang et al. [7] introduced the integrated region matching (IRM). IRM matches one region with several regions in an image. Region based approaches are very close to the human perception of the image [5,8,9]. One of the major challenges of recent image retrieval systems is how we can measure similarity or dissimilarity among images in a large database. Therefore, researcher trend to build a similarity techniques that measure and order images that are perceptually similar to query image. Similarity is a subjective measure and depends on human perception [10,11]. The similarity concept is, in a general sense, an ambiguous and relative concept for humans [11]. This is due to the fact that human had not got extrinsic similarity measures [12]. Human thinking and similarity computation process in human is very complex [13,14]. From psychological and biological viewpoint, similarity computation process is unknown for scientists. There is a close relation between perception and similarity in human beings [12]. Main problem during understanding image by machine is the distance between high level semantics and low level semantics [2,3,15]. Feedback- based methods and region-based-segmentation methods have been proposed to solve this problem [15,16]. Feedback is an iterative process to distinguish and delete irrelevant images. A region -based retrieval system segments images into the regions (objects) and retrieves the images based on the similarity between the regions [3]. Because every object has a unique semantic, human brain uses a semantic library to distinguish the images. In an unconscious process, human beings rank images based on their objects [17]. Similarity measures are classified into two main categories, first, traditional approaches; second, Fuzzy approaches.

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In the traditional techniques or non- fuzzy techniques, a simple distance between low level features is calculated [2,3]. Manhattan, Euclidean distance and probability based similarity measures are the examples of [3,18,19]. The evolutionary computation and feedback technique are combined to measure this category the similarity of images. A new weighted similarity measure is introduced [8]. They have extracted the salient region and made the similarity between the salient regions and the surrounding regions. Traditional similarity measures cannot properly measure the similarity among the concepts in the data base [6]. In a new segmentation method based on Edge Integrated Minimum Spanning Tree is introduced (EI-MST) [20]. It uses a novel way of generating Minimum Spanning Trees and edge detection results. In a new feature grouping algorithm is introduced, it is good for mobile search. In a new feature kernel hashing is represented. It is useful for large scale image datasets. They make a new view on similarity by using a new framework of multiple feature hashing [21,22].

Most of the best approaches in the similarity measure fall in the fuzzy method category. The theory of fuzzy sets, proposed by Zadeh, has gained the successful application in various fields [23]. Measure of similarity between fuzzy sets, as an important content in the fuzzy mathematics, has gained attention from researchers for their wide application in real world. Many measures of similarity between fuzzy sets have been proposed during the last decade. For example, Chen proposed a similarity function. Wang proposed new fuzzy similarity measures on fuzzy sets and elements. After introducing Intuitionistic fuzzy sets (IFS) by Attanassov, many similarity measures are designed based on IFS [2]. An inclusion measure is a pairwise relation between two fuzzy sets, which indicate the degree to which one fuzzy set is contained in another one and is generalized in the inclusion relation. There are many successful applications of fuzzy inclusion measure such as, rough set data analysis [24], fuzzy relational database [25], and fuzzy concept lattice theory [26]. In this paper, we propose a novel fuzzy similarity measure, which is based on monotonic inclusion measure in the Fuzzy Set Theory. One of the main benefits of each similarity measure is that how much its performance is close to the human mind. Similarity measures in humans have three properties which are the reflection, symmetry and transitivity. A similarity measure approach that contains these properties has a good efficiency like human minds. Because our new method has these three properties, thus, it can measure similarity like the human brain and this is the one reason of superiority of our method compared to the other fuzzy methods. If we measure the similarity among images as like as human mind, the performance of CBIR systems can be increased [2,3,27]. Because image objects contain many concepts, one can make a relation between the regions and the objects based on the two following primary assumptions.

1. In a human visual system, objects play a main role and the important objects are placed in a center or near the center of images. So we assume that important objects are located at the near of image center [5].
2. We assume that important objects in an image tend to occupy larger areas. Since the probability of existence of objects in a larger area is greater than a smaller area, the calculation of region areas has helped us to recognize the objects [5].

This work is carried out in two stages, in the first stage, we segment an image into several regions and three low level features (color, texture, shape) are extracted. In this stage, we extract two new features, the region area and region location. Region area and region location help us assign objects to the regions and combine the regions that may include one or more similar objects. In the second stage, a novel fuzzy similarity measure based on Fuzzy Monotonic Inclusion (FMI) measure is done. Then, in order to make similarity vectors, feature vectors are mapped in a mathematic fuzzy inclusion model. Finally, we have tested our approach (i.e. FMI) on Label Me databases and we have compared the results of our approach with UFM and Fuzzy Histogram approaches. The experimental results have shown that the precision which is achieved from our approach is higher than the other methods. The rest of this paper is organized as follows: In section 2, we describe the structure of our CBIR system. In section 3, we speak about the inclusion theory and similarity, and then a fuzzy inclusion algorithm to calculate the similarity measure is presented Section 4. Describes the experiments we have performed and provides the results. And, finally, we talk about the conclusion and future work in section 5.

II. SYSTEM OVERVIEW

The image retrieval process is done in three phases: feature extraction, clustering and fuzzy regions and similarity calculating using Fuzzy Monotonic similarity. The scheme of our image retrieval system can be seen in Figure 1.

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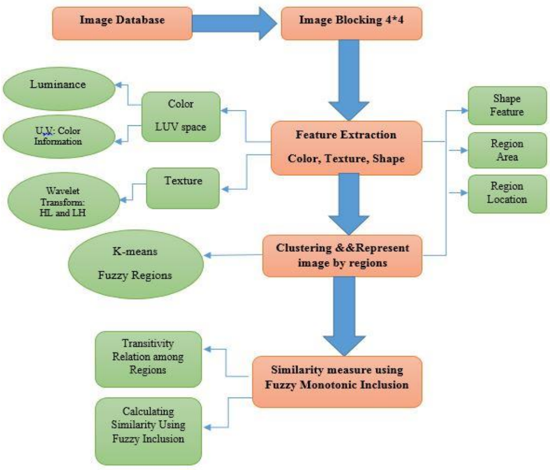

Figure 1: The scheme of our image retrieval system.

2.1 Feature Extraction

In the first step, the image is divided to the blocks and then, low level features including the color, texture and shape are extracted. The system partitions the image into small blocks. A feature vector is then extracted for the image block. The block size is chosen to compromise between texture effectiveness and computation time. Smaller block size may preserve more texture details, but increase the computation time as well [5]. In our system, each block has 4×4 pixels. Feature extraction process has been performed in two steps. First: we extract six features for each block. Three of them are the average color components in a LUV color space where L encodes luminance and U and V encode color information. The other three represent energy in the high frequency bands of the wavelet transforms [28]. Various frequency bands are affecting the representation of texture [29]. Shape and region features are extracted after the image converted to the regions. After the feature extraction, we make the feature vector. Region area is calculated based on the sum of blocks in every region. Region location is subtraction of region center and image center.

2.2 Image Representation By Fuzzy Regions

In the first step, we segment images using K-means algorithm [30], K- means is used to cluster feature vectors into several classes and every class corresponds to one region. The k-means algorithm is a well-known statistical classification algorithm [30] and it is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem [31]. If variables are huge, then K-Means most of the times computationally faster than hierarchical clustering. The computational complexity of most hierarchical methods are O(n2), whereas K- means is only of the order O(Kn), where K is the number of clusters and n the number of observations [32]. For an image with the set of feature vectors F={fi, 1⩽i⩽number of blocks}, F is portioned into C groups{ F1,… FC} and consequently, the image is segmented into C regions {R1…..RC}. Because clustering is performed in the feature space, blocks in each cluster do not necessarily form a connected region in the images. This way, we preserve the natural clustering of objects in textured images and allow classification of textured images [33]. The K- means algorithm does not specify how many clusters to choose. We adaptively select the number of clusters C by gradually increasing C until a stop criterion is met. The average number of clusters for all images in the database changes in accordance with the adjustment of the stop criteria. One of the disadvantage of K-means is initialization, to avoid this problem, we initialize K- means with K=2 and continue to meet stop criteria. All regions are converted to fuzzy regions, therefor Cauchy fuzzy membership function is selected to be use in the process. High computational efficiency is the main advantage of Cauchy function [34]. Figure 2 illustrates the Cauchy function [5].

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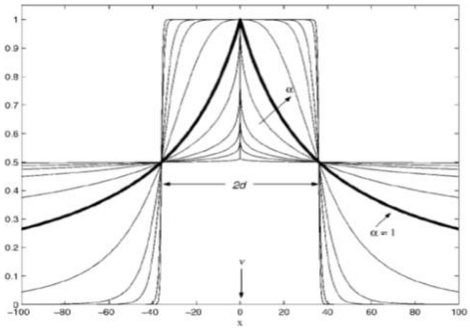

Figure 2: Cauchy function.

The Cauchy function defines as:

$$C(x) = \frac{1}{1 + (\frac{|x - v|}{d})^{\alpha}}$$

Where, v is the center of the function or fuzzy set or region, d represents the width of the function and α is the smoothness of function, d and α >0 . To begin, we set the Cauchy parameters with d=36, v=0 and α varying from 0.01 to 100 [5]. When α=0, the degree of membership is always=0.5. By using Cauchy function, the membership degree of one region is calculated to the whole image. For this, the two following equations are used:

$$d = \frac{2}{c(c-1)} \sum_{i=1}^{c-1} \sum_{k=i+1}^{c} | f_i - f_k |$$

$$\text{Membership (f)} = \frac{1}{1+(\frac{|f-fj|}{d})^{\alpha}}$$

Where, c is the number of regions. At this point, the fuzzy regions and the fuzzy degree of every region are calculated. In the next step, a conceptual relation between regions in an image by using transitivity property of fuzzy inclusion is made. If region (1) has the inclusion relation with the region (2) the region(2) has inclusion relation with region(3), then region(1) and region(3) have inclusion measure. This can be understood from (5),(6),(7) equations. Thus, a fuzzy membership relation is made among all image regions. We use this conceptual relation to compare target image and the query image. In the next stage, a similarity relation between the regions of query image and the regions of the target image is made. We extract the two new features from every region, region area and Region location. Algorithm.1 represents the detail of clustering and K-means. D_f is the average distance between cluster centers. D_h is the average distance between shape features. C is the number of regions.

Algorithm 1. An Algorithmic view on clustering using k- means

1- Generate image blocks, 4*4 blocks
2- B← Number of blocks
3- For i= 1 to B
4- Extract feature vector f_i for block i
5- K=2, D[1]← 0
6- While K≤ M
7- Run K- means and generate K clusters
8- C← k
9- For j=1 to c
10- Compute the mean f_i for each cluster j

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11- J=1, D[k]← $\sum_{i=1}^{B} min_{j\le c}\left\|f_i - f_j\right\|^2$
12- If D[k]<ε_1 or D[k]- D[k-1] <ε_2
13- K← $k+1$
14- D_f,d_h← 0
15- For j=1 to c
16- For i= 1 to c-1
17- For j=i+1 to c
18- $D_f=d_f+\left\|f_i - f_j\right\|$
19- $D_h=d_h+\left\|h_i - h_j\right\|$
20- $D_f \leftarrow \frac{2d_f}{c(c-1)}$, $d_h \leftarrow \frac{2d_h}{c(c-1}$

III.FUZZY MONOTONIC INCLUSION SIMILARITY MEASURE: THE PROPOSED METHOD

3.1 Fuzzy Inclusion Theory

Since the fuzzy set was introduced by Zadeh, many new approaches and theories treating imprecision and uncertainty have been proposed [24]. The concept of inclusion measure between two fuzzy sets is proposed in gradual relations between the objects which have been studied in detail [35]. The similarity measure, the inclusion measure, and the entropy of fuzzy sets are the three important topics in the fuzzy set theory. The inclusion measure of the fuzzy sets indicates the degree to which a fuzzy set is contained in another fuzzy set [36]. Researchers investigate Inclusion measure from axiomatic and constructive view. Sinha and Dougherty [37] introduced an axiomatic definition of the inclusion measure of fuzzy set. Inclusion measure has also been introduced successfully into fuzzy concept lattice theory. Inclusion measure and similarity measure have been used widely in knowledge processing [38]. Qiu et al. addressed an uncertainty analysis method with different inclusion measures for the intelligent systems and other systems such as the fuzzy relational databases In order to construct appropriate similarity measure; we must pay more attention to Fuzzy inclusion measure. In general concept, inclusion is a relation between sets. The fuzzy sets emphasize on the morbid definition of the boundary of sets, in which the relation of “belong to” and “not belong to” between elements and sets in the fuzzy set theory are characterized by the membership degree. Monotonic fuzzy inclusion measure is an equivalence relation and has the reflexive and symmetric and transitive properties [39].

3.2 The Mathematical Layout of The Proposed Method

In this section, firstly the mathematical layout of our proposed method is expressed, and then we speak about Fuzzy Inclusion Similarity measure. FMI has three major properties that are mentioned in the following section: we assume A and B are the regions or a set of regions in a query and target image and S is the

S(A,A)=1 for all A $\in$ Image Reflective principle (1)
S(A,B)=S(B,A) for all A,B $\in$ Image Symmetric Principle (2)
S(A,B) and S(B,C) $\Longrightarrow$ S(A,C) for all A,B,C $\in$ Image Transitivity Principle (3)
S(A, A^c)=0 A^c is an empty region (4)

In the Principle 1, 2 and 3 mathematical principle of equivalence in similarity measure is expressed. In the Principle 3, an important relation among at least 3 regions has been expressed. Principle 3 can be developed to cover all the regions of the images. In the following principles, basic relations in the Fuzzy Inclusion measure [37] are seen:

A,B,C,D $\in$ Image, If A$\subseteq$B$\subseteq C \subseteq D$ then S(A,D)$\le S(B,C)$ (4)
Inclusion (A,B)=1 if A$\subseteq B$ for all regions in images (5)
If A$\subseteq B$ $implies\ Inclusion(A,B) = 1\ \ for\ all\ A,B \in images$ (6)
If A$\subseteq B, then\ inclusion(B,C) \le inclusion(A,C) and\ inclusion(C,A) \le inclusion(C,B), for\ all\ A,B,C\ \in image$
(7)

The similarity among regions, A, B, C, D are gained based on the above relation [37]. It is shown in the equation (8).

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$$s(A,B) \wedge s(C,D) \leq s(A \cap C, B \cap D) \qquad (8)$$

On (6), the transitivity principle in the inclusion relation is represented. From the equation (6), relation inclusion among all regions of image is perceived. For more information refer to [37].

3.3 Fuzzy Monotonic Inclusion Similarity Measure

We assign a feature vector to every region. Feature vector is made from three parts, low level features, region area and region location. The main duty of every similarity measure method is to represent the conceptual closeness of the target and the query regions and it is obtained by calculating the differences between feature vectors. We make a new weighted similarity measure by using equation (7) and equation (8) and inner production between equation (8) and two new features, the region location and the region area.

We called Equation (9),T, then similarity is :

$$Similarity(query, target) = T(q,t)L(r_{ij})A(r_{ij}) + \left[\left(1 - L(r_{ij})\right)\left(1 - A(r_{ij})\right)\right]T(q,t) \qquad (9)$$

The proposed similarity measure is computed in two stages. First, area fuzzy location of each region is computed. Second, the inner products among T(q,t) and $L(r_{ij})$and $A(r_{ij})$is computed. L(ri,j) represents the region location of i and j for the query image (q) and the target image (t) image, respectively. A(ri,j) represents the region area i and j for query image (q) and target image (t) image, respectively. The first the part of above equation trends to compute the shape properties and second part refers to textured images or images that their shape properties are not important. The proposed method has two advantages: First, we make relation between regions by using transitivity. Second, our proposed method includes two new features in relation with regions, area region and location region. Algorithm 2 represents the inclusion measure process. L(f) describe the similarity in color and texture and L(h) describe the similarity in shapes.

Algorithm 2. Similarity vectors and Inclusion measure process

1- For i= 1 to C_q
2- $L(f_q,f_t)[i] \leftarrow \frac{d_f + d1_f}{d_f + d1_f + min_{j=1,ct}\|f_i - f_j\|}$
3- For i=1 to C_t
4- $L(f_q,f_t)[i+C_q] \leftarrow \frac{d_f + d1_f}{d_f + d1_f + min_{j=1,Cq}\|f_i - f_j\|}$
5- Inclusion Measure Function( ) {
6- If($R_{(q,i)} < R_{(t,i)}$) then
7- Inclusion (R_q ,R_t)=1
8- Else
9- Inclusion(R_q ,R_t)=0
10- IF membership($R_{(q,i)} \leq R_{(t,i)}$) then
11- R_q=R_t
12- $Similarity(query, target) = T(q,t)L(r_{ij})A(r_{ij}) + \left[\left(1 - L(r_{ij})\right)\left(1 - A(r_{ij})\right)\right]T(q,t)$ }

IV. EXPERIMENTAL RESULTS

We implanted the FMI on Label me, a Real world image data set with 163000 images. For each image, the features, locations and area of all regions are stored. We compared FMI with UFM (Chenand and Wang) and Fuzzy histogram (Waken et al.). In section 4.1, we introduce the test bed. Section 4.2 presents accuracy of FMI. The Precision Analysis is presented in section 4.3.

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4.1 Test Bed

The system is tested on an object based image database (from Label Me), including 163,000 pictures which are stored in JPEG format. The following is a list of qualities that distinguish Label Me from previous works.

- Designed for recognition of a class of objects instead of single instances of an object. For example, a traditional dataset may have contained images of dogs, each of them in the same size and orientation. In contrast, Label Me contains images of dogs in multiple angles, sizes, and orientations.
- Designed for recognizing objects embedded in arbitrary scenes instead of images that are cropped, normalized, and/or resized to display a single object.
- Complex annotation: Instead of labelling an entire image (which also limits each image to containing a single object), Label Me allows annotation of multiple objects within an image by specifying a polygon bounding box that contains the object.
- Contains a large number of object classes and allows the creation of new classes easily.
- Diverse images: Label Me contains images from many different scenes.
- Provides non-copyright images and allows public additions to the annotations. This creates a free environment.

We used 22 Semantic classes (Table 1). We used 80,000 pictures from label Me. The results are compared with UFM (Unified Feature Matching) scheme and fuzzy Histogram. Experimental results showed that the proposed scheme outperforms the UFM and Histogram approach.

Class number	Class name		Class number	Class name
1	Night-outdoor		12	Italy- Outdoor
2	animals		13	industry
3	Village		14	Organization- indoor
4	House-indoor		15	Dinner- indoor
5	sport		16	Bedroom-
6	Boston Park		17	Hotel room
7	Spanish Roads		18	Harvard street
8	Forest park		19	Football field
9	airport		20	Mexico
10	New York city		21	Italy
11	birds		22	Boston

Table 1: Label me classes.

4.2 The Accuracy of The Proposed Scheme

In this section we investigate the precision, the investigation has been performed in two part; first, we discuss the images with one object. Second, we discuss the precision at images with multi objects.

4.2.1 Investigate the precision of proposed method in the images with one object:

First, we investigate semantic classes with one object. For example, in the semantic class of Animal and Birds, just one main conceptual object exists. In this two classes, the precision of the proposed method and UFM (unify fuzzy feature matching) is similar and the performance of proposed method and UFM is closely, while the precision of Fuzzy Histogram is lower than our proposed method and UFM. This may indicate that UFM and the proposed methods are working based on the Fuzzy region and therefore, in images that include one object, the performance of UFM and the proposed method are good and similar.

4.2.2 Investigation of the precision of the proposed method in the images with multi objects:

In this section, we discuss the precision of our proposed method on images with multi objects in comparison with UFM and Fuzzy histogram. 'Boston' and 'Village 'are the two instance of the semantic classes with multi objects. The accuracy of the proposed method is higher than UFM and Fuzzy Histogram. This result shows, our method can make

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semantic relation among the regions and the extract concepts and therefor objects from the image are recognized. Our proposed Fuzzy similarity measure is successful to extracts semantic from regions. To investigate the effect of the two new features on the performance of the proposed method, we eliminate these two features and the similarity is calculated again. We have seen the accuracy of the proposed method was reduced to 25%. This results show, the region area and the region location help us recognize the objects. Because Fuzzy Histogram method uses the global features of the images, its performance in object recognition is not good and in images with multi objects, the precision of Fuzzy Histogram is low. It seems with increasing semantic concept of the images, the precision of the Fuzzy Histogram faces with sharp decline. The precision results are shown in the Figures 3 and 4.

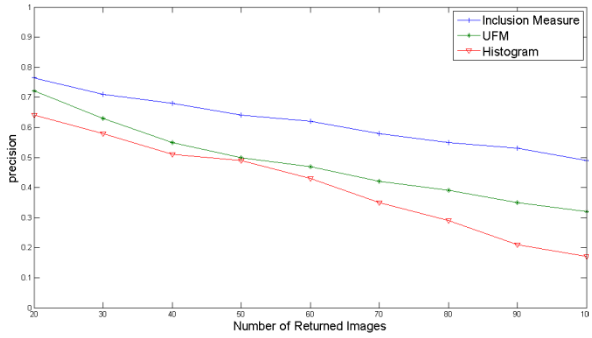

Figure 3: Comparing the accuracy of FMI with UFM and fuzzy histogram.

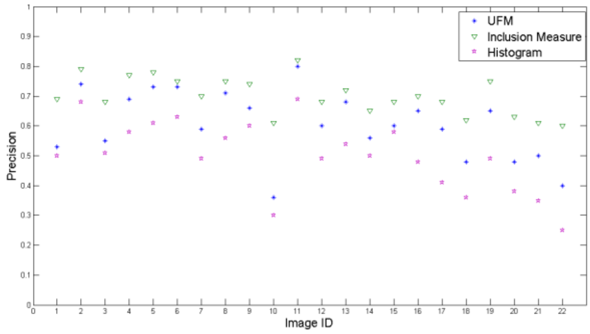

Figure 4: Comparing the FMI method with UFM and fuzzy histogram on accuracy for each class.

4.3 Precision Analysis

For each of the twenty two image categories, the average precision is plotted in Figure 4. The image category identification number is indicated in Table 1. The accuracy of the proposed scheme is higher than UFM scheme and Fuzzy Histogram.

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Figure 5: Label me image samples.

V. CONCLUSION AND FUTURE WORK

In this paper, we presented a new Fuzzy monotonic similarity measure. This method works based on the fuzzy logic. We classified images to fuzzy regions and two new features extracted for every region, the region area and the region location. These two new features are mixed with the low level features, color, texture and shape and a new feature vector for every region is made. Experimental results show, the region location and the region area are helpful in object extraction. Thus, the performance of Fuzzy Monotonic Inclusion Measure on images with multi objects has increased. Moreover, our proposed methods make the semantic relations among the regions by using transitivity property and help the system to extract semantic from every image. We have compared our proposed similarity method with UFM and Fuzzy histogram. The experimental results show the superiority of our proposed method. The results are tested on the conceptual and object based Dataset, Label Me. Since, this approach has paid attention to the objects and image fuzziness, its performance is close to human perception (Figure 5).
The system may be improved in the following ways:

- We aim to process our system with Relevance feedback algorithms to enable the system to be better in retrieval process.
- Our system can be extended to process medical images. We can define a new conceptual vector for every region and finally compare conceptual vector for every region. These vectors are a basement for similarity process.
- Improve segmentation process; In order to enable our system to overcome to weakness of K-means, we can extend segmentation process by using fuzzy C-means and fuzzy C- regression model.
- Improve our Fuzzy inclusion similarity with type-2 fuzzy sets.
- Membership function, In order to improve our system, a new fuzzy membership function can be applied on relation between regions.

Our system can be useful in medical image retrieval systems, search engines and satellite image processing.

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