Image Classification and Retrieval Based on Crisp and Fuzzy Ontology

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ABSTRACT**:** *This paper analyzes the crisp and fuzzy ontology for image classification and retrieval. It addresses a question of how fuzzy ontology performs as compared to crisp ontology in retrieving images. The approach is based on building ontology of natural scenes using Protégé for querying in more natural way and then integrating fuzzy logic to improve the image retrieval.*

Keywords: Semantic Web, Ontology, Fuzzy Ontology

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1. Introduction

As images are of great importance nowadays in every domain such as medical, astronomical, fashion, architecture etc there is a need for better image classification and retrieval for growing user interest.

Earlier images were classified using low level features like texture, color, spatial location and retrieval was either text based or content based. Text based image retrieval sometimes provide too many redundant images or no image at all. Content based image retrieval is based on visual contents but visual similarity does not mean semantic similarity. Semantic image annotation is arguably a more natural way of describing image features and ontology based retrieval has the potential to satisfy the user requirements better as it's more focused on semantic content. Ontology is an abstract representation of the domain. Ontologies are based on crisp logic that is either belonging to a particular concept or not but the problem in crisp ontologies is how to represent non-crisp data like tasty or cheap food etc within the ontology definition. The idea of fuzzy set and fuzzy logic theory was first proposed by Zadeh, as a mean of handling uncertainty. It has been shown that fuzzy ontology reduces the gap between the human understandable knowledge and machine understandable logic. In this paper, we investigate fuzzy logic in ontology in order to define fuzzy ontology and conclude how it performs as compared to crisp ontology. In case of crisp ontology, instance either belong to a concept or not but in case of fuzzy ontology instance does not fully belong to a concept instead has a membership value being an instance to that concept.

This research work is build on work of Zia[16]. He used Vogel's[17] dataset of 700 natural scenes images. Vogel divide the image into 10*10 grids and identify nine local concepts and annotate the grids using those concepts and build a model that categorize images into six major categories namely forest, coasts, sky_clouds, waterscapes, landscape with mountains, field. Zia worked for queries like find images with mountains and sky on top. He investigated three types of spatial relationships that is relative size of each of the concept occurrences, Allen's calculus was used for describing the 13 relations namely before, meet, contains etc between the concepts. Also he apply chord pattern to each grid row.

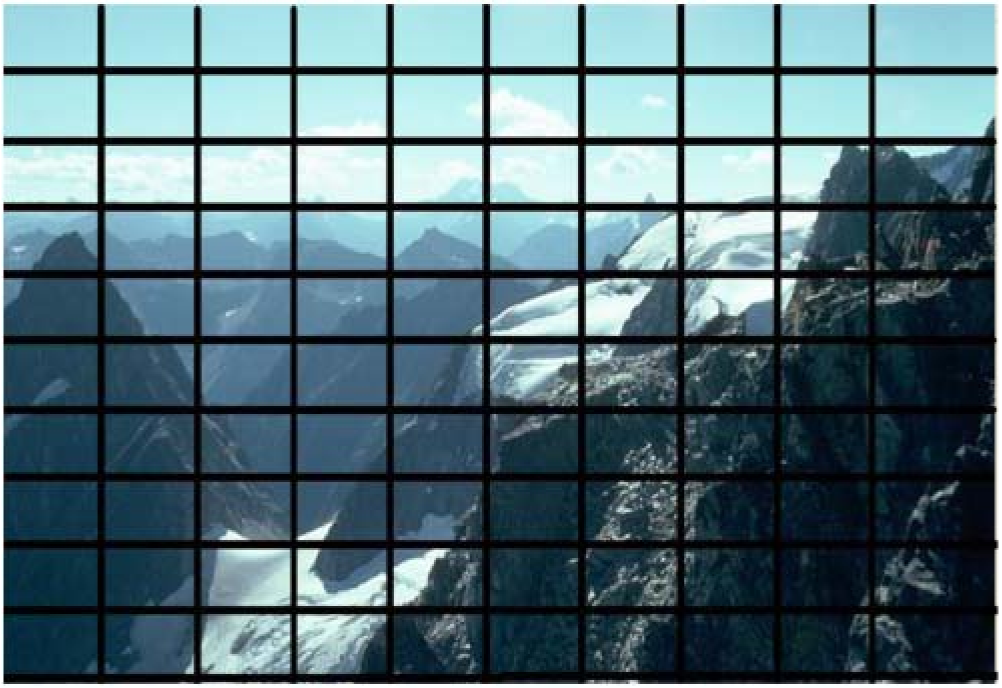

Figure 1. Image division into 10 *10 grids

Build on Zia's work, we classify the image based on crisp ontology and then integrate the fuzzy logic in it.

2. Literature Survey

Most of the work on image retrieval was based on low level feature description and image categorization. Ontologies are better solution for image classification and retrieval.

In [1], author presents a system for semantic search based on ontology that provides the domain knowledge. But retrieval performance is not shown. In [2], author proposed a concept based technique utilizing a personalized ontology and spatial ontology. In [3], author proposed a system that is based on ontology for accessing heterogeneous data of cultural heritage. In [4], author proposed a hybrid system that is based on ontology and can find images through keywords that were used to describe images in ontology and can find similar images based on visual similarity or can use both techniques. In [5], author proposed three layered in-progress system architecture for better retrieval of images based on ontology. In [6], author provides a complete description of ontologies and shows their usefulness in image description and retrieval. He builds the ontology for photography exhibition and shows better retrieval results. In [7], a detailed survey of different retrieval techniques is mentioned. Author started from low level image feature extraction, then measure the similarity of the content, and at the end map them to high-level features. In [8], author proposed an annotation system in which he applied the spatial relationship between the labeled regions or objects and then used this information in building ontology. In [9], author proposed an automated system for image annotation based on ontology. The system extracts the high-level concepts and inference rules from images using ontology. In [10], author presents an ontology based system that aims to reduce the semantic gap by annotating the images using concepts of the ontology and then retrieving the data. In [11], Document summarization and text-and content-based image retrieval is done. In [12], author presents an automated system for image classification and for retrieval the system compare the indexes and it can retrieve the queries like ball, sky, beach etc. In [13], author proposed a system for image retrieval that is based on arbitrary regions. He proposed a two layered architecture, first he extracts low level features from arbitrary regions and then map low level features to high level concepts for searching images.

The research works mentioned above focuses on crisp ontology. Since crisp ontology is a two-valued logic either an instance belong to a concept or not, the relative importance of particular mapping is really tough using crisp logic as it's different for different users. Fuzzy ontology is a better solution for overcoming this problem.

3. Methodology

The proposed system model is shown below:

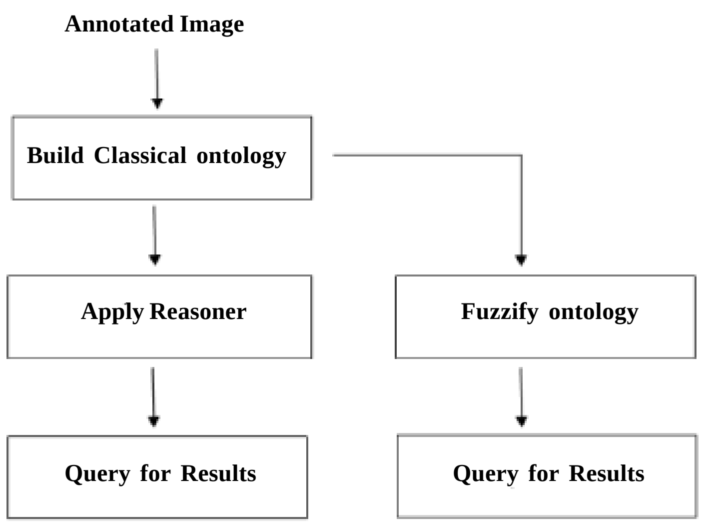

Table 1. System Model

Step by step description is as follows:

3.2 Building Classical Ontology

As we are working on natural scenes so the major entities are Images, Grids, Category and Concept. Images are further classified into images namely 2010, 2011, 2012 etc. Each image is divided into 100 grids so we classify grids as 2010.00, 2010.01 2010.02 etc. Grids are annotated with 9 local concepts namely mountains, sky, snow, grass, foliage, water, field, trunks, flowers and sand. Next we classify Concepts into above mentioned concepts. Every image is assigned a category namely Lwm, Sky_Clouds, Waterscapes, Coasts, Field, Forest. Taxonomy is shown below:

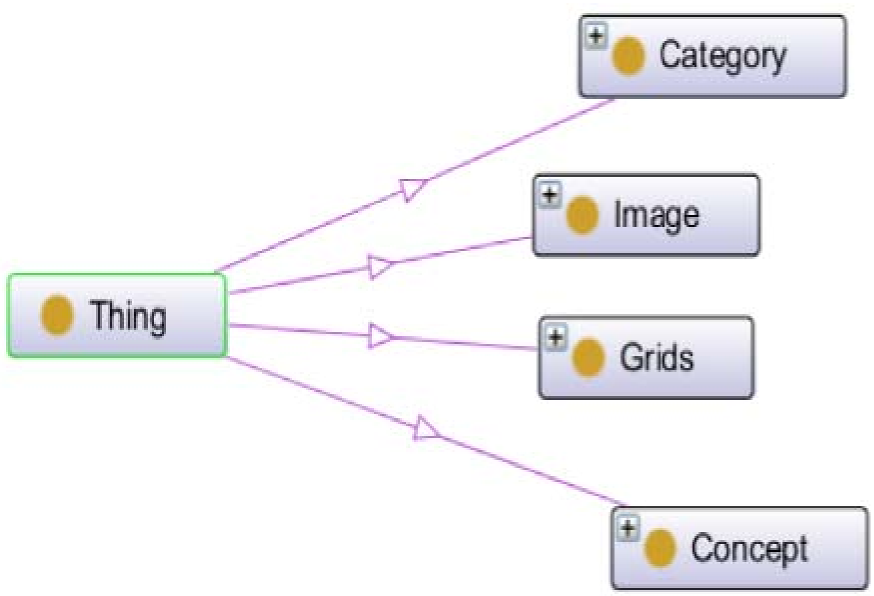

Figure 2. Taxonomy

After identifying classes, next step is to define the properties that hold these classes. Properties represent relationship. Three types of properties exists:

1) Object property: Link an individual to an individual

2) Data type property: Link an individual to data type value.

3) Annotation property: Used to add information to classes, individuals etc.

The following table defines the object properties:

Property	**Domain**	**Range**
isDividedInto	Image	Grids
isPartOf	Grids	Image
hasConcept	Grids	Concept
isConceptOf	Concept	Grid
hasCategory	Image	Category
isCategoryOf	Category	Image
isOnTopOf	Grid	Grid
isOnBottomOf	Grid	Grid
isOnLeftOf	Grid	Grid
isOnRightOf	Grid	Grid

Table 2. Defining properties

Inverse properties are also defined. IspartOf is inverse of isDividedInto, isConceptOf is inverse of hasConcept and isCategoryOf is inverse of hasCategory etc.

Next we define the data type property hasOccuranceValueMountain. Domain of this property is Image and its value is of integer data type.

After defining properties create Axiom. Axiom LargeMountion is defined as:

LargeMountain= Image and (hasOccuranceMountain some (integer[> 60] and integer[<= 80])) (1)

Similarly MountainsWithTreesOnLeft is defined as:

MountainsWithTreesOnLeft = Image and (isDividedInto some (Grids and (isOnleftOf some (Grids and (hasCocept value Foliage))) and (hasCocept value Mountains))) (2)

Similarly we had defined VeryLargeMountain, TreesOnLeftOfMountains, LargeAmountOfWater etc.

Instance of Image	**isDividedInto**	**hasCategory**
Image1	Image1.00,Image1.01, Image1.02,Image1.03 ………	LandWithMountains
Image2	Image2.00,Image2.01, Image3.02,Image4.03 ………	Forest

Table 3. Defining instances of Image

3.2 Define Instances

Add instances to Image and define properties.

Similarly we define the instances of Category and Concepts. Now apply reasoner to check any consistency problem and open Descriptive Logic query engine to query on ontology. If we write LargeMountain in the query engine then it will retrieve those images having mountains occurance value > 60.

We can also retrieve images that have mountains with trees on left and images that contains very large or small mountains etc.

3.3 Fuzzify Ontology

As the ontology build is based on crisp set we can fuzzify the ontology for retrieval accuracy. As in fuzzy logic instance does not fully belong to a set instead it is assigned a membership value that ranges in [0-1].

We start by defining the fuzzy concepts and datatype as we did in classical ontology.

Fuzzy Datatype LargeMountainOccurance is defined by right shoulder function as shown below:

Instance of is Grids	PartOf	hasConcept
Image1.00	Image1	Mountains
Image1.01	Image2	Mountains
. . .		

Table 4. Defining instances of Grids

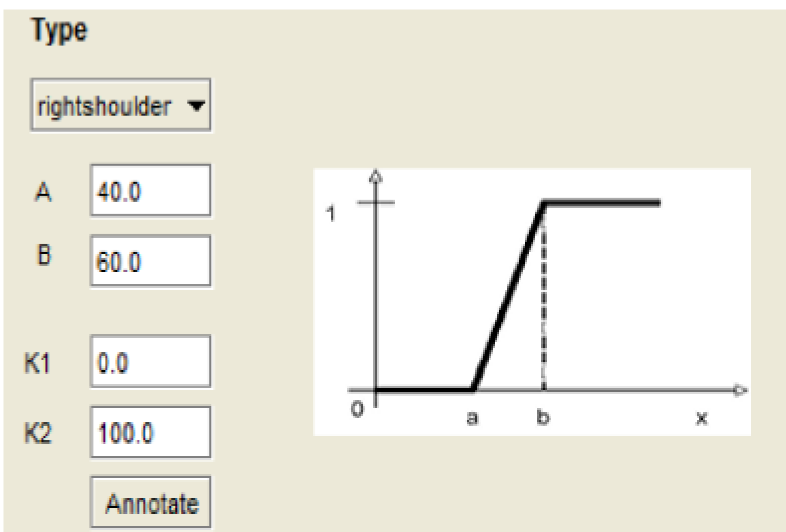

Figure 3. Right Shoulder Function for defining Large Mountain Occurance

Similarly we define small mountain occurrence by left shoulder function respectively as shown in the following figures:

Fuzzy concept LargeMountain and, SmallMountain are defined as:

LargeMountain= Image ∏ ∃ hasOccuranceMountain.*LargeMountainOccurance*

SmallMountain= Image ∏ ∃ hasOccuranceMountain.*SmallMountainOccurance*

We also define the fuzzy concept VeryLargeMountain by first defining the modifier Very as Linear function and then applying the modifier to base concept LargeMountain.

Very is defined as linear(0.8) as shown below:

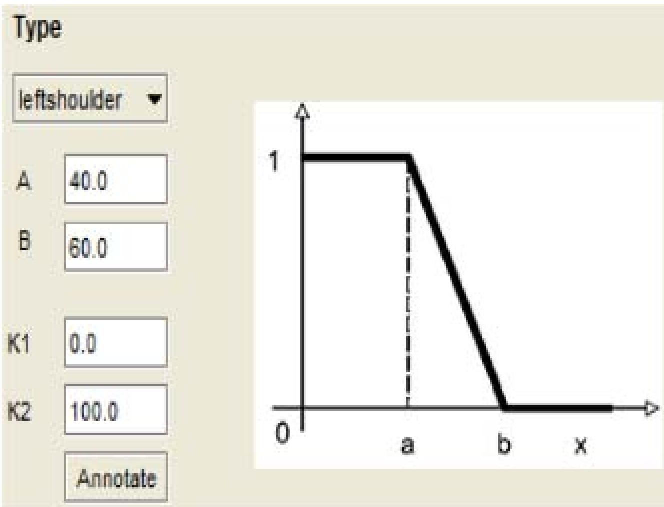

Figure 4. Left Shoulder Function for defining Small Mountain Occurance

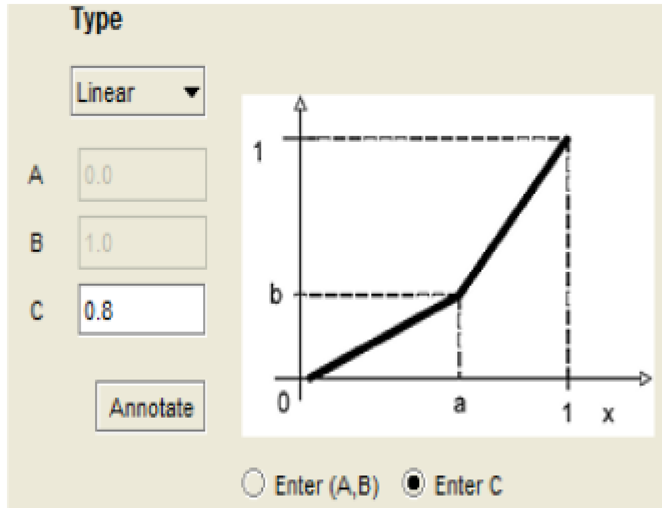

Figure 5. Linear Function for defining Very

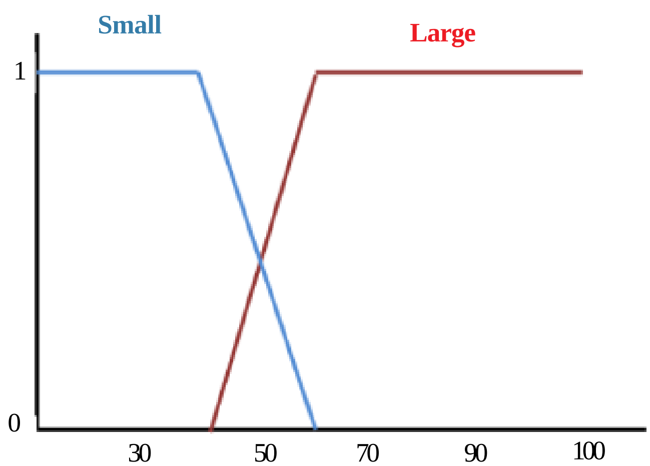

Figure 6. Small and Large Mountain Occurance

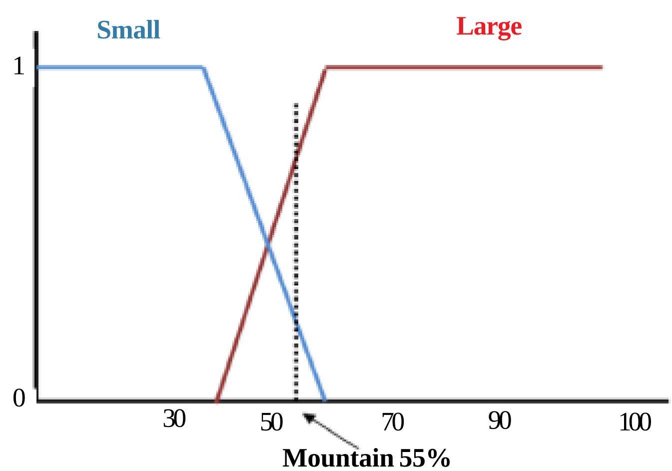

Figure 7. 55% mountain occurance defined on Large and Small Mountain Occurance Function

Applying this modifier to base concept means we are setting a threshold of 0.8. Images that belongs to LargeMountain class and have truth value greater than or equal to 0.8 are considered as containing very large mountains.

VeryLargeMountain= Very(LargeMountain)

4. Experimental Results

In classical ontology instance either belongs to a class or not but in fuzzy ontology the query engine provides the truth value of an instance belonging to a particular class.

For Example, image named Image1 contains 55% mountains and if we want to retrieve small mountains then its degree of truth in belonging to Small Mountain class is 0.25 and its degree of truth in belonging to LargeMountain class is 0.7. But in case of classical ontology this image will not be considered as belonging to LargeMountain class as defined in (1).

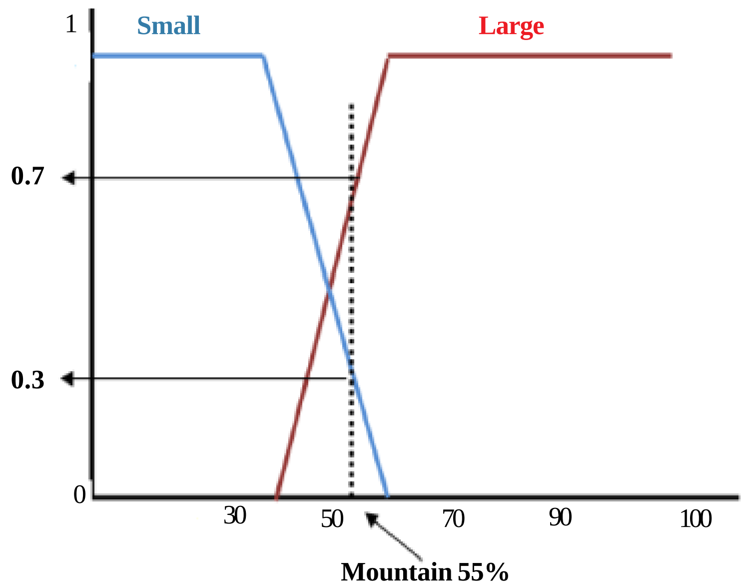

Figure 8. Membership values assigned on Small and Large scale

5. Conclusion and Future Work

Fuzzy Ontology approach provides a better way for image retrieval as compared to crisp ontology. Classifying the image using ontology requires labor work but it improves retrieval accuracy to much extent. In future we want to extend the vocabulary since this system relies on limited vocabulary and will try to automate the annotation process.

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