A Fuzzy Ontology Model for Qualitative Spatial Reasoning

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Abstract- **Spatial relations and spatial reasoning are essential in cognitive systems. Human uses qualitative words of natural language to represent his perceptions about spatial structures. Computational systems which want to manipulate this perception need to be able to convert quantitative data into qualitative ones and vice versa. These perceptions are normally described by imprecise, vague and relative concepts. On the other hand, fuzzy ontologies are proposed to handle vague or imprecise ontological knowledge. In this paper we propose a new model based on fuzzy ontologies to support qualitative spatial reasoning. It proposes a method of representing qualitative data as fuzzy attribute values in an ontology.**

I. INTRODUCTION

Spatial structures and spatial reasoning are essential to perception and cognition. For being able to reason about spatial features of different entities first we must find a way to store this kind of information.

Ontology is an explicit, formal specification of a shared conceptualization [1]. Ontologies are the knowledge backbone of many knowledge based and intelligent systems. They contain concepts and their properties and relations in a specific or general domain. They may also contain axioms to enable reasoning and inference over the knowledge.

Crisp ontologies which are the most common type of ontologies represent crisp knowledge while fuzzy ontologies allow some parts of this knowledge to be fuzzified. Fuzzy ontologies are proposed to handle vague or imprecise ontological knowledge. The vagueness and so the fuzziness may appear in concepts, in their attributes values, in the relations among them or in the axioms.

Human performs wide variety of physical and mental tasks without any measurements. He uses propositions drawn from natural language to represent his perception. Natural language use linguistic values for variables which provide qualitative data to represent people perceptions. For example a physical object may be “close to” or “far away” from another without mentioning the quantity of distance. The temperature of an object may be "low" or "high" and it may be "cold" or "hot". In these cases we talk about the qualitative knowledge, while when we say the temperature is $28^{\circ C}$ we are presenting quantitative knowledge.

Human can also compare qualitative knowledge about different entities easily. He can convert qualitative knowledge to an approximation of corresponding quantitative data and vice versa. These enable him to reason with qualitative knowledge as well as quantitative one.

In this paper we propose a model to represent qualitative knowledge and its relation with quantitative one to enable reasoning. Although this method works for any type of knowledge, in this paper we focus on spatial knowledge and show examples from size attribute.

The rest of this paper is organized as follows. In the next section we introduce fuzzy logic and fuzzy ontology. In the third section we propose our model and in the fourth section we discuss reasoning over our model. The last section describes some related work and compares them with our model.

II. FUZZY LOGIC AND FUZZY ONTOLOGY

Fuzzy logic, a super set of crisp logic, is based on fuzzy set theory and is used for approximate reasoning with imprecise information [2]. While in classical set theory elements either belong to a set or not, in fuzzy set theory [3] elements can belong to a set to some degree. Fuzzy set theory exploits a membership function to allow membership of an item in a set to be any real number between 0 and 1. It provides a way to use linguistic values to model natural language uncertainties. While variables in mathematics usually take numerical values, in fuzzy logic applications, the non-numeric linguistic variables are often used to facilitate the expression of rules and facts.

There are several kinds of membership functions including trapezoidal, triangular, left-shoulder and right-shoulder. The trapezoidal functions which are mainly used in this paper, can be defined as a four-tuple (q_1, q_2, q_3, q_4) where

$$q_1 \le q_2 \le q_3 \le q_4 \quad (1)$$

$$\mu_Q(u) = \frac{u - q_1}{q_2 - q_1} \qquad \forall u \in [q_1, q_2]$$

$$\mu_Q(u) = 1 \qquad \forall u \in [q_2, q_3]$$

$$\mu_Q(u) = \frac{q_4 - u}{q_4 - q_3} \qquad \forall u \in [q_3, q_4]$$

$$\mu_Q(u) = 0 \qquad \forall u \in [k_1, q_1] \cup [q_4, k_2]$$

As an example consider the linguistic variable “height”. It may have values such as short, medium-height or tall for the concept “human”. The membership function is shown in Fig 1.

Each linguistic variable has some linguistic values and each linguistic value has a membership function. The great utility of using linguistic variables is that they can be modified via linguistic modifiers such as very, slightly and extremely applied to the primary terms. The linguistic modifiers are used to alter the strength of the original linguistic values. The membership function of the conjunction of a modifier and a linguistic value is defined as a function of the membership function of the base linguistic value.

Two kinds of modifiers are defined including restrictive (such as very) and expansive (such as slightly) modifiers. And two approaches are used for defining the membership function of the modifiers; (1) powering and (2) shifting functions.

Also two different interpretations of modifiers (such as “very”) are presented, including inclusive and non-inclusive interpretations. In inclusive interpretation the fuzzy set “very large” is included in the fuzzy set “large”. Thus, for every x, if x is very large then x is large. On different conditions, using powering or shifting modifiers are recommended in this interpretation.

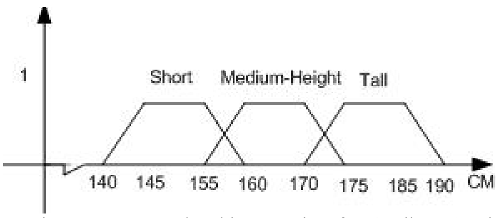

Fig1. Fuzzy Membership Function for Attribute “Height” of Concept “Human”[1].

In non-inclusive interpretation, neither the fuzzy set “very large” is included in “large”, nor is “large” in “very large”. Large and very large denote two different (overlapping) categories. It is the interpretation of listener, When we say x is large, the listener assumes that x isn't very large, because if the latter case was right we would have used the more informative utterance x is very large. Shifting modifiers are proposed to be used in this interpretation [4].

Fuzzy Ontology is simply an ontology which uses fuzzy logic to provide a natural representation of imprecise and vague knowledge and ease reasoning over it [5]. To provide a fuzzy ontology definition we must first decide about the fuzzy elements. According to the reasoning requirements, different parts may be fuzzy. For example one may need to reason about how strong a relation is between two entities. So the relations should be fuzzy. Or one may need to reason about concepts’ attribute values. Like, if the size of a “very big cat” is bigger than a size of “an extremely small elephant”. So here attributes are getting fuzzy.

Each element gotten fuzzy can get a value including a fuzzy number or a fuzzy linguistic value. In the latter case, a membership function is assigned to each linguistic value and the linguistic value may get modifiers.

Fuzzy logic has been applied in some domains like semantic web services [6] or information retrieval [7]. To enable our system to reason about qualitative spatial data we propose to use fuzzy ontology to represent knowledge. In the next section, we propose our model for fuzzy ontologies to support qualitative spatial reasoning.

III. The Proposed Model

In this paper, we formally define fuzzy ontology (with a special focus on fuzzy properties) as a 4 tuple $O_F = (C, P^C, R, A)$ where,

- C is a set of concepts.
- P^C is a set of entity properties that can be represented as a 8 tuple $p^c(c, p, v_p, g_p, n_p, q_p, h_p, f)$ where
  - c is an ontology concept.
  - p is the property name.
  - v_p is a set of values of the property.
  - g_p is a set of membership functions assigned to the members of v_p.
  - n_p is a set of membership degrees assigned to v_p.
  - q_p models linguistic modifiers(which is optional) .
  - h_p is a set of membership functions assigned to each modifier.
  - f is a restriction facet such as type or cardinality. The type may be {Integer, float, etc}. Cardinality defines the upper and lower limits on the number of values of the property.
- R is a set of relations between concepts.
- A is a set of axioms.

[1] It should be mentioned that as the figure shows, in this paper, we suppose that objects are in their normal ranges, So a Human being with the height of 195 cm is not tall but very tall. Without this assumption, we have to define the function in a way that all heights more than 185 be considered as tall (with μ=1) and all heights less than 145 be considered as short (with μ=1).

For example concept human has the property height (P) which can have linguistic values short, medium-height and tall (v_p) with their assigned membership function (g_p) as shown in Fig 1.

And optionally a set of modifier such as very (q_p) can be assigned to the base linguistic values with their assigned membership functions (h_p). One possible h_p for modifier very could be defined in this way:

$\mu_{Very-X} = (\mu_X)^2$ Where X is the linguistic value like short

Different entities in the real world have different membership functions for their linguistic values. For example, for a concept "tree" the linguistic values for the property "height" have the following membership functions (Fig 2)[2] which are different from the ones for human (Fig 1). So the system should know that fuzzy values in different concepts have different quantities.

As another example consider the attribute "size". if the reasoner wants to compare the size of "a very big cat" and "an extremely small elephant", it not only should contain the data that can quantize the big cat and small elephant but also it needs to understand the relation between very small, extremely small and small.

For enhancing fuzzy ontology with fuzzy attributes, we define a Complex Data Property with structures shown in Fig 3.

In this figure the notion of complex data property is introduced. The complex data property includes a linguistic variable and two parts of information about it, the crisp part and the fuzzy part. The crisp part (CrispInfo) contains crisp value which shows the ranges of the crisp value for concepts and the real crisp value (if any) for instances. It also contains the unit of measurement with which the value is measured. The fuzzy part (FuzzyInfo) includes linguistic values and the modifiers. Linguistic value and modifiers are concept attributes (which get value in the concept) while linguistic values membership degree is an instance attribute (which get value in the instances).

The membership function can be kept as a string or as the numbers defining the function (see the fuzzy logic section). In this paper the latter approach is used. For example a trapezoidal, triangular, left-shoulder membership function can be kept with four, three and two numbers respectively.

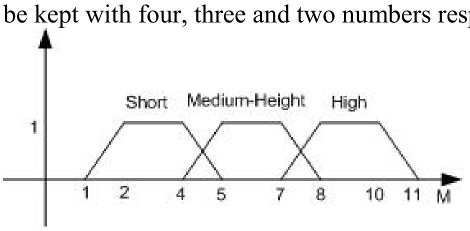

Fig 2. Fuzzy Membership Functions for Attribute "Height" of Concept "Tree".

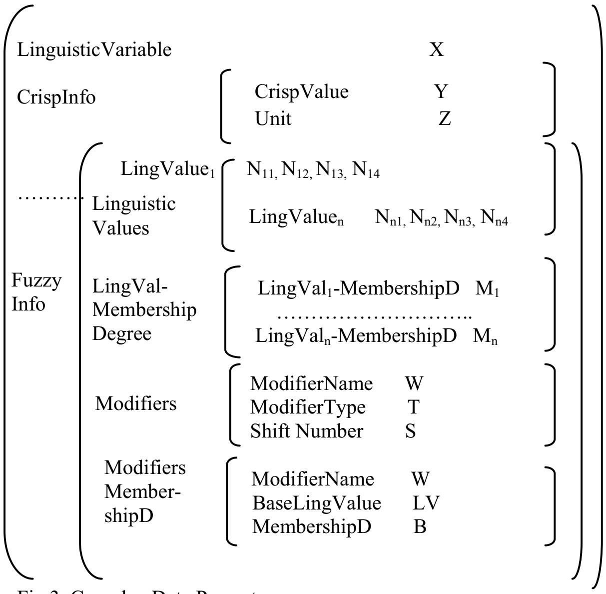

Fig 3. Complex Data Property

The other parts of FuzzyInfo are the modifiers. In this paper the non-inclusive interpretation is chosen. So each modifier contains 3 fields including modifier-name, modifier type (expansive or restrictive), and modifier shifting number which shows how the membership function of the modified linguistic value could be computed. As an example the complex data property for the attribute "size' of the concept "laptop" is shown in Fig 4.The numbers show that the diagrams in Fig 5 are assigned to linguistic values "small", "medium" and "large" for the size attribute of a laptop.

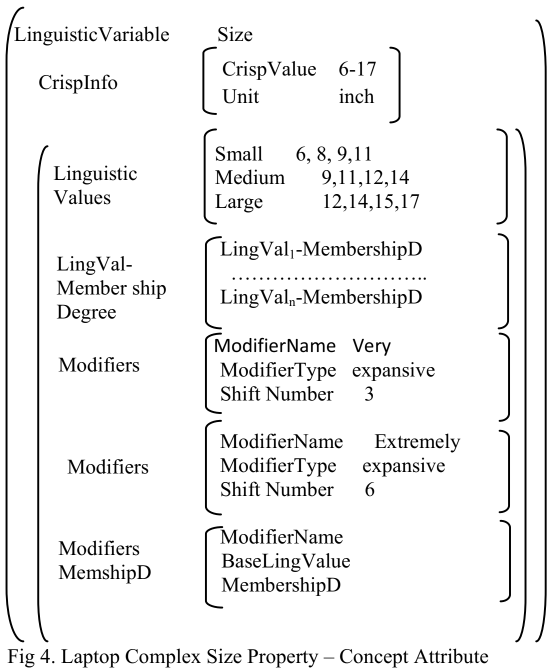

Fig 4. Laptop Complex Size Property – Concept Attribute

[2] These ranges are for a supposed kind of tree

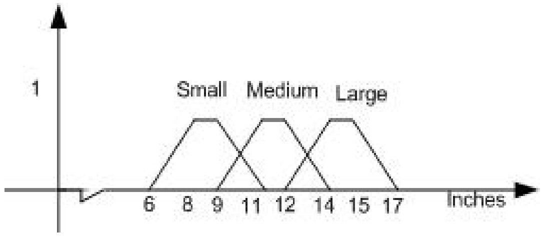

Fig 5. Fuzzy Membership Functions of Concept" Laptop".

For a laptop of size 10 inches named "Laptop#10", the following values are computed.

$$\mu_{Small} = \frac{11-10}{11-9} = 0.5 \quad (2)$$

$$\mu_{Medium} = \frac{10-9}{11-9} = 0.5$$

$$\mu_{Large} = 0$$

For computing the membership function of an instance to the conjunction of a modifier and a linguistic value the following approach is applied. As we mentioned, non-inclusive interpretation was chosen for the modifiers, so a shifting operator is applied. A central linguistic value is defined. Combining with expansive modifiers, the linguistic values which are located right to the central linguistic value will be shifted to right and the linguistic values located at the left of the central linguistic value will be shifted to left and vice versa is done for restrictive modifiers. In the example the modifier part shows that modifier "very" is a shifting modifier by number 3. So the combination of "very" with the linguistic value "small" will shift the membership of small by the number of three to left. "very small" is shown in Fig 6. The following membership functions are computed for Laptop #10.

$$\mu_{Extremely-Small} = 0 \qquad \mu_{Very-Small} = 0 \quad (3)$$

$$\mu_{Very-Large} = 0 \qquad \mu_{Extremely-Large} = 0$$

But for a supposed laptop of size 5 inches, it is very small. Fig 7 shows the example of the fuzzy instance attributes for instance Laptop#10.

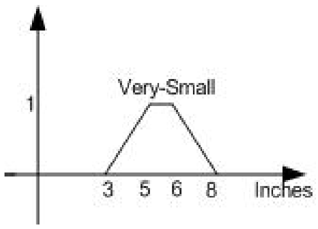

Fig 6. Fuzzy Membership Functions of "Very Small" for Concept "Laptop"

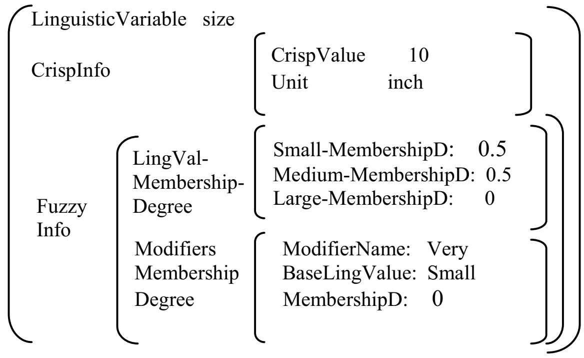

Fig 7. Laptop#10-Complex Size Property- Instance Attribute.

IV. Qualitative Spatial Reasoning in the Proposed Model

In the previous section, keeping membership functions with their assigned linguistic values were proposed. Although this model enhances qualitative reasoning for all kinds of attributes, the focus of this paper is on spatial reasoning. So the attribute gotten fuzzy should be a kind that contains spatial information like those we presented in our examples such as width, height, size, volume, etc.

First of all we should find a way to represent the complex data property in a machine readable format. We propose an extended version of OWL called E-OWL for representing it. As in Fig 8 it is shown.

```
< E-OWL: ComplexDataProperty    DataProperty1>
   < E-OWL: LinguisticValues>
      < E-OWL:  LingValue1>
         < E-OWL: Type>Triangular/Trapezoidal,…</Type>
         < E-OWL: AssignedFunction> a, b, c <AssignedFunction>
       </ E-OWL:  LingValue1>
      <E-OWL:  LingValue2>……</ E-OWL LingValue2>
      < E-OWL:  LingValuen>……</ E-OWL:  LingValuen>
   < E-OWL:  /LinguisticValues>
   < E-OWL: Modifiers>
      < E-OWL: Modifier1>
         < E-OWL: Type>Restrictive/Expansive</Type>
         < E-OWL: ShiftingNumber>S#</ E-OWL:ShiftingNumber>
      </ E-OWL: Modifier1>
       < E-OWL: Modifier2>…….</ E-OWL: Modifer2>
   < /E-OWL: Modifiers>
</ E-OWL: ComplexDatProperty>
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Fig 8. Formal Representation of Complex Data Property.

This formal representation can be translated to the structure presented. So a reasoner which implements fuzzy membership functions can answer these questions.

- For a concept, the reasoner can find typical value of its different linguistic values. For example, by the membership function of small laptop included in complex data property - shown in Fig 4 – it can be inferred that the typical size of a small laptop is between 6 to 11 inches.

- For a concept, the reasoner can find the membership functions of its attribute linguistic values, for example the reasoner can return the curve of “small laptop” as shown in Fig 5.
- Having the crisp value of an instance of a concept, the reasoner can find the value of the instance linguistic values. As it was shown for Laptop#10. The reasoner does this inference by using the membership functions of different linguistic values discussed in the previous bullet.
- The reasoner can combine a linguistic value with modifiers as shown for “very small”.
- Between two concepts with the same fuzzy attribute, the reasoner can compare their linguistic values. For example fuzzy attribute values for the concept “computer mouse” are shown in Fig 9. The reasoner can infer that a large mouse is between 8 to 11 centimeters. And a small laptop is between 6 to 11 inches. For comparing this quantities first it should converts their units. The Ontologies which contain Measurement Unit information like MUO (Measurement Unit Ontology) [8] can be used here. That’s why we keep measurement units too. Because for every concept the typical unit for measuring it’s attributes is different. After converting the units of data, it can infer that a large mouse is smaller than a small laptop.

These preliminary inferences can be combined to have more powerful spatial reasoning. For example, in different situations the reasoner can infer, if the two objects may contact or they will be disconnected. For example if the question is “putting a very large mouse, a medium sized keyboard and a small monitor on a medium sized desk, do they physically contact or not”, the reasoner can infer the typical size of a medium sized desk, very large mouse, small monitor and medium sized keyboard. By a simple comparison of these sizes the question can be answered.

Also it can infer If one of the objects can be put on top of the other or not, if they are identical or not, if one of them can contain another or not. As an example it answer that a big matchbox can be put on a small desk but a small cat can’t be put inside a very large matchbox. To reason about the ability to put object A inside object B the system should infer some knowledge such as:
(1) the inner volume of B is larger than the outer volume of A. this can be done easily using the volume attribute of the concepts or by applying formulas to calculate the volumes according to the dimensions[3].

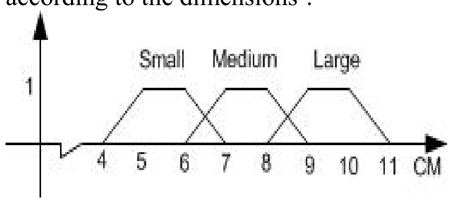

Fig 9. Membership Function of Attribute Size for Computer Mouse

[3] Volume calculation should be added to the reasoner in further work

(2) none of the dimensions of A is larger than all dimensions of B. this can also be inferred from our model if its data is available[4]

V. Related work

A. Fuzzy Ontology

The concept of fuzzy ontology has attracted some attention in the last years. Some researchers have worked on application of fuzzy ontologies for enabling a system to work with quality. As an example we can mention Abulaish and Dey [9] who propose a fuzzy ontology framework in which a concept descriptor is defined as a fuzzy relation. The relation encodes the degree of a property value, in a <property, value, qualifier, constraints> framework. The proposed fuzzy ontology structure is applied in an information retrieval application. For matching a pair of <value, qualifier> tuples, the overall effect is also influenced by the distance between the qualifiers as it is influenced by the distance between value pairs.

Zhai et al. [10] propose a three layer model for fuzzy ontologies. This model includes three parts: concepts, properties of concepts and values of properties. Property values can be ordinary values or linguistic values of fuzzy concepts which are defined by fuzzy linguistic variable ontology. For example in an e-commerce application the concept “customer” has property “income” which can get values “little”, “low”, “middle”, “high”, etc.

Developing fuzzy ontologies was of much interest too. For example Tho et al. [11] propose Fuzzy Ontology Generation Algorithm (FOGA) based on fuzzy set theory and formal concept analysis (FCA) for developing a fuzzy ontology. In FOGA the uncertainty information is represented by a real number for the membership values in the range of [0 1]. Lee et al. [12] propose a fuzzy development method and use the fuzzy ontology in news summarization.

The first group [9, 10] contains the list of linguistic values and uses the order relation between them for matching the tuples and query expansion. Membership functions are not used in them. The second group [11, 12] add fuzzy weights for the fuzzification and fuzzy linguistic values are not used in them. To give a method which can handle linguistic values, we apply both the membership functions and linguistic values in this paper.

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B. Qualitative Spatial Reasoning

Qualitative spatial reasoning has been the topic of researches too. Esterline et al. [13] propose a fuzzy spatial logic, which takes the single relation connected-with (connected (x, y)) as primitive and derive all other spatial relations based on it. Membership functions are defined for each spatial relation and principles for defining linguistic

[4] In complex real world problems we should consider other parameters such as the shape, stuff and flexibility of two objects too. If we have this information we can represent them in our model as well. But the inference mechanisms for them are out of the scope of this paper.

variables with spatial relations as linguistic values are presented.

Straccia [14] presents a fuzzy DL ALCF(D) for fuzzy spatial reasoning, by supporting both fuzzy spatial relations of the "region connection calculus" as well as application domain dependent fuzzy spatial relations such as "close", "far", "over".

Hudelot et al. [15] introduce an ontology of spatial relations, enriched by fuzzy representations of these relations in the spatial domain. This fuzzy spatial relation ontology is then used to support a reasoning process in order to recognize structures in images.

These researches model fuzzy spatial relations, an important type of knowledge that enhances spatial reasoning between elements. Also they discuss about reasoning with fuzzy spatial relations. Ref [13] proposes a fuzzy version of an existing crisp spatial logic and [14] uses a fuzzy DL for representing spatial relations while [15] use an ontology of spatial relations.

In this work we add qualitative attributes to the existing knowledge in the crisp ontology. Spatial relations can be inferred from this qualitative attributes.

VI. CONCLUSION AND FURTHER WORKS

In this paper, a fuzzy ontology model which provides qualitative spatial reasoning was proposed. As an example we discussed how the attribute "size" in the proposed ontological model can be fuzzified to support spatial reasoning.

Fuzzy membership functions can be put in the ontology manually or automatically. For further work we plan to enhance the model with some tasks to provide the fuzzy membership functions automatically. To do this we are going to adopt IR algorithms to develop a module for finding crisp values of attributes for different concepts in the ontologies. Also we plan to work on clustering algorithms for mapping the crisp values of the attributes to the fuzzy linguistic values and generate their membership functions.

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