

# Modelling and Managing Ambiguous Context in Intelligent Environments

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**Abstract**—To achieve a more robust and flexible context data management, it is important to take into account aspects usually neglected, like the uncertainty and vagueness of the context data. By considering this information it is possible to attain a more precise picture of the environment, thus leading to a more accurate inference process. To achieve these goals we present an ontology that models the ambiguity in intelligent environments and a data fusion and inference process that takes advantage of that extra information to provide better results.

*Keywords-component; fuzzy logic; uncertainty; vagueness; context; data fusion; inference*

## I. INTRODUCTION

Intelligent environments host a diverse and dynamic ecosystem of devices, sensors, actuators and users. Modeling real environments taking certainty for granted is usually a luxury that a context management framework cannot afford. Reality, at hence the context, is ambiguous. Sensors and devices are not perfect and their measures carry a degree of uncertainty, several thermometers in the same room can provide conflicting measures of the temperature and there always exists the human factor. Not every user can provide the exact temperature they want for their bath, most of them will only say that they want it “warm”. For this reason, when developing smart spaces and ambient intelligence application, it is important to address ambiguity in order to model more realistically the context. To provide our systems of this feature, we have centered our work in two aspects of the ambiguity: uncertainty and vagueness.

We use uncertainty to model the truthfulness of the different context data by assigning to them a certainty factor (CF). This way we can know the reliability of each piece of information and act accordingly. This data also allow us to create a more robust data fusion process to resolve the problem of the existence of multiple providers for the same piece of information in the same location. On the other hand, vagueness helps us to model those situations where the boundaries between categories are not clearly defined. This usually occurs when users are involved. Different users will have different perceptions about what is a cold room or a noisy environment. We have addressed this problem using fuzzy sets to model the vagueness.

In this paper we will describe the three main components of the ambiguity conscious frameworks we have developed. First we will describe the ontology created to model the uncertainty and vagueness in context. Then we will discuss

the data fusion process that takes place to infer the real status of the rooms using multiple measures. Finally we will describe the implemented inference mechanism that processes ambiguity as a whole, combining vagueness and uncertainty. The outline of the paper will be the following. In Section 2 we will analyze the related work, in Section 3 we will describe the created ontology and in Section 4 we will explain how the framework works and the inference that takes place within it. Finally in Section 5 we will expose the conclusion and the next steps we intend to take.

## II. RELATED WORK

Several authors have worked into combining indetermination or vagueness with ontologies. An extensive survey can be found in [1]. In the case of the indetermination, in [2] authors present a probabilistic generalization of OWL called PR-OWL based in MEBNs (Multi Entity Bayesian Networks) which allows the combination of first order logic with Bayesian logic. This ontology represents the knowledge as parameterized fragments of Bayesian networks. In [3] authors propose another probabilistic generalization of OWL called BayesOWL which also uses Bayesian networks. Authors suggest a mechanism which can translate an OWL ontology to a Bayesian network, adding probabilistic restrictions when building the network. The created Bayesian network maintains the semantic information of the origin ontology and allows ontological reasoning modeled as Bayesian inference. Authors in [4] describe another integration of OWL with Bayesian networks, a system named OntoBayes. It uses an OWL extension annotated with probabilities and dependencies to represent the uncertainty of Bayesian networks. These probabilistic extensions are not confined to OWL only, in [5] an extension for OWL Lite is discussed and in [6] and [7] extensions for RDF are presented.

Several authors have also addressed the combination of the vagueness (represented as the usage of fuzzy sets) with ontologies. In [8] authors analyze how SHOIN could be extended adding the possibility of using fuzzy sets (f-SHOIN). They also propose a fuzzy extension for OWL. In [9] authors describe a fuzzy extension for SROIQ(D) and present an Fuzzy OWL2 Ontology. In [10] a fuzzy ontology for the management of medical documents is discussed. This ontology can store different membership values. Additionally the author has created a mechanism based in the occurrence of keywords in the title, abstract or body of the document to calculate the membership value of the different

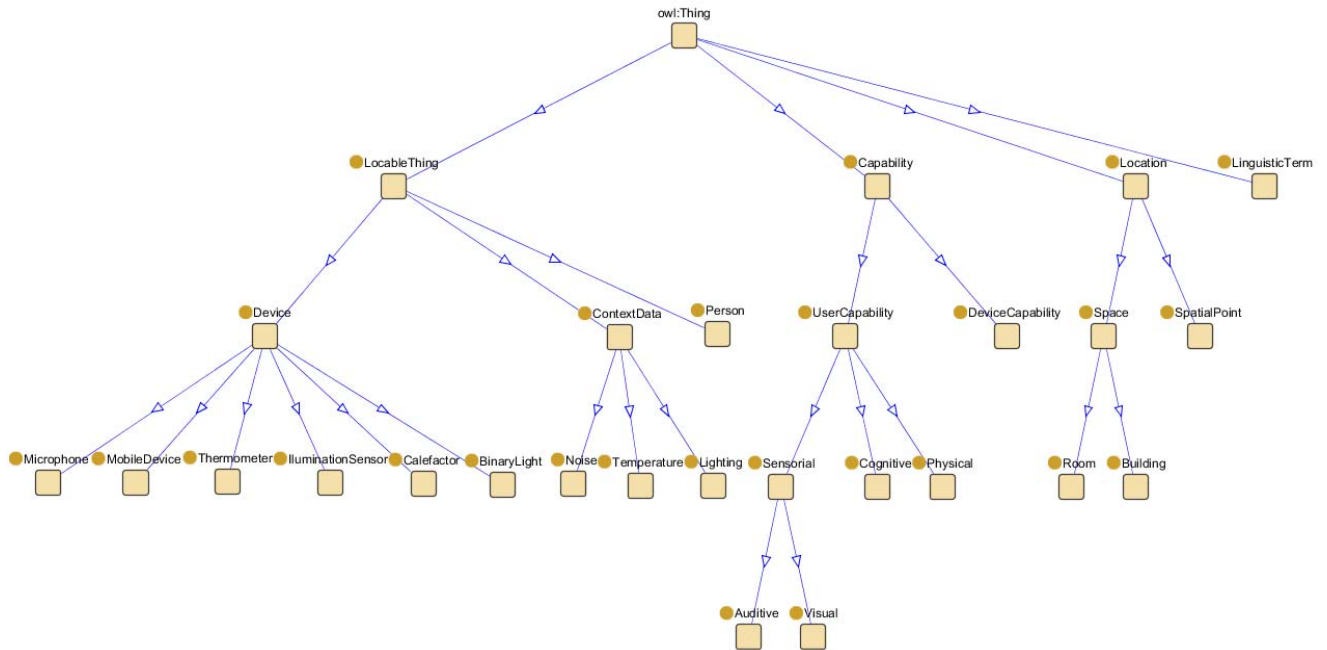


Figure 1 Subset of the main ontology concepts

categories. In [11] authors describe a fuzzy ontology used to automatically create summaries of news articles. Authors have also created a mechanism for the automatic creating of the fuzzy ontology based on the analysis of the news. Finally in [12] authors propose a mechanism to create automatically fuzzy ontologies. The created ontologies include the membership values of the different terms.

### III. AMBI<sup>2</sup>ONT: AN ONTOLOGY FOR THE AMBIGUOUS REALITY

One of the problems we encountered modeling context data in previous projects was the use of the uncertainty and vagueness of the gathered information. In the Smartlab project [14] none of this information was used, which led to a loss of important data like the certainty of the measures taken by the sensors. In the Imhotep framework [13] we started using fuzzy terms to describe a small part of the context (the capabilities of mobile devices and users) in a human-friendly manner. Our objective with the work presented in this paper was to develop a framework capable of managing the ambiguity and incertitude that often characterizes the reality. To do this we have created an ontology that models these concepts. As shown in Figure 1 the main elements of the ontology are:

- *Location*: The subclasses of this class represent the location concepts of the context. In our system we have three types of locations, points, rooms and buildings.
- *LocableThing*: The subclasses of this class represent the elements of the system that have a physical location. It contains 3 subclasses: the *Person*

subclass represents the users, the *Device* subclass models the different devices of the environment and the *ContextData* subclass models the measures taken by the sensors. As we will explain in the next section there are two types of measures, those taken by the devices and the global measures for each room calculated by our data fusion mechanism. Figure 1 shows a subset of the type of context data taken into account in the ontology.

- *LinguisticTerm*: This class models the fuzzy linguistic terms of the values of the context data. The ontology only stores the linguistic term and membership value of each individual of context data. Currently the ontology does not model the membership functions and rules used by the inference engine.
- *Capability*: The subclasses of this class model the capabilities of users and their mobile devices. One objective of our framework is to be integrated with the Imhotep Framework that allows creating adaptive user interfaces that react to these capabilities and the changes on the context.

#### A. Modelling uncertainty and vagueness

Our ontology models two aspects of the ambiguity of the context data, the uncertainty (represented by a certainty factor, CF) and the vagueness (represented by fuzzy sets). Uncertainty models the likeliness of a fact, for example “*the temperature of the room is 27°C with a certainty factor of 0.2 and 18°C with a certainty factor of 0.8*” means that the value of the temperature is more probably 18°C (but it cannot be both of them). In the case of vagueness it represents the

degree of membership to a fuzzy set. For example “*the temperature of the room* is cold with a membership of 0.7” means that the room is mostly cold. In Figure 2 it can be seen how those values are stored in the ontology. Each ContextData individual has the following properties:

- *crisp\_value*: the measure taken by the associated sensor. In our system a sensor is defined as anything that provides context information.
- *certainty\_factor*: the degree of credibility of the measure. This metric is given by the sensor that takes the measure and takes values between 0 and 1.
- *linguistic\_term*: each measure has its fuzzy representation, represented as the linguistic term name and the membership degree for that term.

This can be seen in the example shown on Figure 2. The temperature measure has a crisp value of 32°C with a certainty factor of 0.7. After processing that crisp value with the associated membership functions our system has inferred that the membership degree for cold is 0, for mild is 0.2 and for hot is 0.9; so the room is mainly hot.

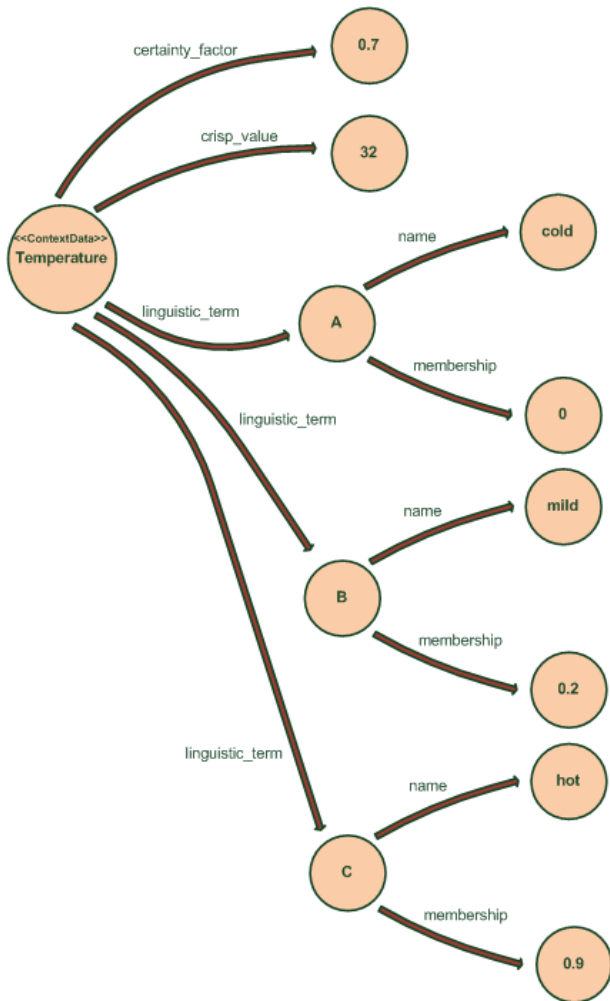


Figure 2 Example of the ambiguity data for a temperature measure stored in the ontology

#### IV. SEMANTIC CONTEXT MANAGEMENT FOR AMBIGUOUS DATA

The semantic context management is done in four steps (see Figure 3): add the measures to the ontology, process the semantic and positional information, apply the data fusion mechanism and process the ambiguity contained in the data.

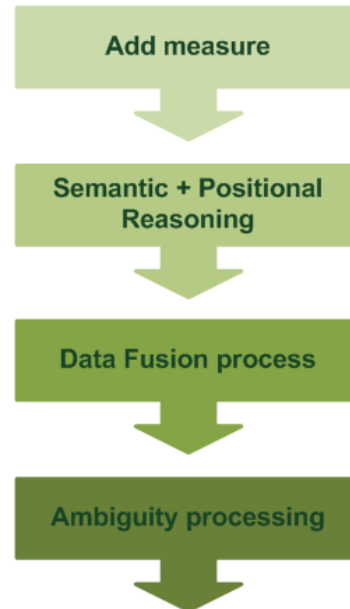


Figure 3 Context management process

##### A. Adding the measure

To add a measure to the ontology the sensor must provide the measure type, its value, location and a certainty factor. We assume that each sensor knows its certainty factor based on its type and manufacturer. We also assume that the certainty factor of the sensor can change over time depending on the environment (e.g. a thermometer can be pretty accurate for temperatures between -10°C and 50°C but the measure quality can degrade outside that range). For that reason the sensor certainty factor is not stored in the ontology when the sensor registers itself.

##### B. Processing the semantic and spatial data

Once the measures have been added, we apply a semantic inference process to achieve two goals: make explicit the hidden implicit knowledge in the ontology and infer the positional information of each measure. To do this we use two different sets of rules: the semantic rules and the spatial heuristic rules.

To make the semantic reasoning less cumbersome we implement a subset of the RDF Model Theory [19] and the OWL Model Theory [20]. An example of the used rules can be seen in Figure 5.

```

[LOCATIONINFERENCE-DeviceItemPlacedIn:
  (?thg1 rdf:type <http://www.morelab.deusto.es/ambOnt.owl#DeviceItem>),
  (?thg1 <http://www.morelab.deusto.es/ambOnt.owl#placedIn> ?loc1),
  (?loc1 rdf:type <http://www.morelab.deusto.es/ambOnt.owl#SpatialPoint>),
  (?loc1 <http://www.morelab.deusto.es/ambOnt.owl#isContainedBy> ?area1)
->
  (?thg1 <http://www.morelab.deusto.es/ambOnt.owl#placedIn> ?area1)
]

[LOCATIONINFERENCE-ItemColocatedWithPersonInPoint:
  (?thg1 rdf:type <http://www.morelab.deusto.es/ambOnt.owl#DeviceItem>),
  (?thg1 <http://www.morelab.deusto.es/ambOnt.owl#placedIn> ?loc1),
  (?loc1 <http://www.morelab.deusto.es/ambOnt.owl#x> ?x1),
  (?loc1 <http://www.morelab.deusto.es/ambOnt.owl#y> ?y1),
  (?thg2 rdf:type <http://www.morelab.deusto.es/ambOnt.owl#PersonItem>),
  (?thg2 <http://www.morelab.deusto.es/ambOnt.owl#isLocatedIn> ?loc2),
  (?loc2 <http://www.morelab.deusto.es/ambOnt.owl#x> ?x2),
  (?loc2 <http://www.morelab.deusto.es/ambOnt.owl#y> ?y2),
  equal(?x1,?x2)
  equal(?y1,?y2)
->
  (?thg1 <http://www.morelab.deusto.es/ambOnt.owl#colocatedWith> ?thg2)
]

```

Figure 4 Example of the positional inference

```

[rdfs9:
  (?x rdfs:subClassOf ?y),
  (?a rdf:type ?x)
->
  (?a rdf:type ?y)
]

[OWL-InverseOf-A:
  (?x ?prop1 ?y),
  (?prop1 owl:inverseOf ?prop2)
->
  (?y ?prop2 ?x)
]

```

Figure 5 An example of the implemented semantic rules

The spatial heuristic rules are used to infer higher level positional information from the coordinates provided by the sensors. This information comprises data like the room in which the sensor is located; the devices, people and sensors surrounding it and the relative location to other *LocableThing*-s (refer to section 3 for more information about the elements of the ontology). An example of the used rules can be seen on Figure 4. In the first rule a device's area of location is inferred using its (x,y) coordinates. The second rule checks if a device and a person are in the same position.

### C. The data fusion process

Once the location and semantic information of the measures has been inferred and processed the data fusion process is applied. From the previous step we can infer that each room can have multiple sensors that provide the same context data (e.g various thermometers in the same room). Usually the values and certainty factor of those measures do not coincide. To be able to take the proper actions we need to process those differing measures to assess the real status of to room. To tackle this problem we have created a data fusion mechanism that refines those individual measures into

a single global measure for each room. We have implemented two types of strategies for this process: *tourney* and *combination*.

Using the *tourney* strategy the measure with the best CF is selected as the global measure of the room. On the other hand the *combination* strategy has three different behaviors as stated in [15]:

- *Severe*: The worst certainty factor from all the input measures is assigned to the combined measure.
- *Indulgent*: The best certainty factor from all the input measures is assigned to the combined measure.
- *Cautious*: An average certainty factor is calculated using the certainty factor from the input measures.

To determine the combined measure value we weight the individual values using their certainty factors as seen in the following equation.

$$m_{global} = \frac{\sum_{i=0}^n (m_i * cf_i)}{\sum_{i=0}^n cf_i} \quad (1)$$

Where:

- *m*: the measure values.
- *cf*: the measure certainty factor.

In Table 1 we show an example of how the data fusion process works when the *combination* strategy is used:

TABLE 1EXAMPLE OF THE DATA FUSION PROCESS USING THE COMBINATION STRATEGY

	Value	CF	Global Value	CF Severe	CF Indulgent	CF Cautious
M1	18	0.7	19.9	0.6	0.8	0.7
M2	22	0.7				
M3	16	0.6				
M4	20	0.8				

#### D. Processing the ambiguity

As explained previously we model two aspects of the ambiguity: the uncertainty and the vagueness. To be able to reason over this information we have modified the JFuzzyLogic [16] Open Source fuzzy reasoner to accept also uncertainty information. JFuzzyLogic follows the FCL (Fuzzy Control Language) [17] standard for its rule language.

The modified reasoner supports two types of uncertainty, uncertain data and uncertain rules. The first type occurs when the input data is not completely reliable (as seen in the example shown in Table 1). To support this type of uncertain data we have modified the API of the reasoner (see Figure 6).

```
reasoner.addVariable("Temperature1", 18, 0.7);
reasoner.addVariable("Temperature2", 22, 0.7);
reasoner.addVariable("Temperature3", 16, 0.6);
reasoner.addVariable("Temperature4", 20, 0.8);
```

Figure 6 Use of the modified reasoner to process the data of the previous example

The second type of uncertainty takes place when the outcome of a rule is not fixed, for example “if the barometric pressure is high and the temperature is low there is a 60% chance of rain”. To model this aspect of uncertainty we have modified the grammar of the FCL language. An example of the modified rules can be seen on Figure 7.

```
RULEBLOCK No1
  AND : MIN;
  ACT : MIN;
  ACCU : MAX;

  RULE 1 : CF 0.6
    IF PRESSURE IS HIGH AND
    TEMPERATURE IS LOW
    THEN PRECIPITATION IS RAIN
END_RULEBLOCK
```

Figure 7 An example of an uncertain fuzzy rule

Uncertainty and fuzziness can appear in the same rule and influence each other. To tackle this problem we have implemented the inference model described in [18]. This model contemplates three different situations depending on the nature of the antecedent and consequent of the rule and the matching fact: CRISP Simple Rule where both antecedent and matching fact are crisp values, FUZZY\_CRISP Simple Rule where both the antecedent and matching fact are fuzzy and the consequent is crisp and finally the FUZZY\_FUZZY Simple rule where all three are fuzzy.

In the case of the CRISP Simple Rule the certainty factor of the consequent is calculated using the following formula:

$$CF_c = CF_r \times CF_f \quad (2)$$

Where:

- $CF_c$ : the certainty factor of the consequent.
- $CF_r$ : the certainty factor of the rule
- $CF_f$ : the certainty factor of the fact

In the case of FUZZY\_CRISP Simple Rule the certainty factor of the consequent is calculated using the following formula:

$$CF_c = CF_r \times CF_f \times S \quad (3)$$

Where S is the measure of similarity between both fuzzy sets and is calculated using the following formula:

$$S = P(F_x|F'_x) \quad \text{if } N(F_x|F'_x) \\ S = (N(F_x|F'_x) - 0.5) \times P(F_x|F'_x) \quad \text{otherwise} \quad (4)$$

Where:

$$P(F_x|F'_x) = \max \left( \min \left( \mu_{F_x}(u), \mu_{F'_x}(u) \right) \right), \quad \forall u \in U \quad (5)$$

And:

$$N(F_x|F'_x) = 1 - P(F_x|F'_x) \quad (6)$$

Finally in the case of FUZZY\_FUZZY Simple Rule the certainty factor of the consequent is calculated using the same formula than in the CRISP Simple RULE. Currently we do not support this type of combined reasoning for complex rules that involve multiple clauses in their antecedent.

#### V. CONCLUSIONS AND FUTURE WORK

In this paper we have presented an ontology that models the ambiguity of the smart environments and a flexible semantic context management system. Our context management system is able to process the uncertainty and vagueness of the contextual information to provide a more detailed picture of the current state of the user environment. Modeling and managing ambiguity we try to provide a more robust and flexible context management framework. We have also described a data fusion mechanism applied in the case that multiple data sources for the same measure exist in one room. This mechanism relies on the uncertainty information provided by our system to create a global assessment for each room that tries to infer the real situation.

As future work, first we would like to create a mechanism that automatically assesses the certainty factor of a sensor comparing its data with the one provided by other sensors. This will allow us to identify and discard malfunctioning sensors automatically. Secondly we would like to develop an ecosystem of reasoners to distribute the inference process. We hope that this distribution will lead to a more agile and fast reasoning over the context data, allowing us to combine less powerful devices to obtain a rich and expressive inference. Finally we would like to explore the possibility of including uncertainty in the membership functions.

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