AN APPROACH TO MORE RELIABLE CONTEXT-AWARE SYSTEMS BY ASSESSING AMBIGUITY

Taking into Account Indetermination and Vagueness in Smart Environments

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Abstract: Often context-aware systems consider the environment a defined element. Meanwhile reality is full of vagueness and uncertainty. Taking into account these aspects we can provide a more grounded and precise picture of the environment, creating context-aware systems that are more flexible and reliable. It also provides a more accurate inference process, making possible to consider the quality of the context data. In order to tackle this problem we have created an ontology that considers the ambiguity in smart environments and a data fusion and inference process that takes advantage of that extra information to provide better results.

1 INTRODUCTION

Intelligent environments host a diverse and dynamic ecosystem of devices, sensors, actuators and users. Modelling real environments taking certainty for granted is usually a luxury that a context management framework cannot afford. Reality, and 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 with this feature, we have centred 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. These 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.

2 RELATED WORK

Several authors have worked into combining indetermination or vagueness with ontologies. An extensive survey can be found in (Lukasiewicz and Straccia, 2008). In the case of the indetermination, in (da Costa et al., 2005) 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

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Bayesian logic. This ontology represents the knowledge as parameterized fragments of Bayesian networks. In (Ding et al., 2006) 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 original ontology and allows ontological reasoning modeled as Bayesian inference. (Yang and Calmet, 2005) 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. Several authors have also addressed the combination of the vagueness (represented as the usage of fuzzy sets) with ontologies. In (Stoilos et al, 2005) 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 (Bobillo and Straccia, 2009) authors describe a fuzzy extension for SROIQ(D) and present an Fuzzy OWL2 Ontology. In (Parry, 2004) 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 categories. In (Lee et al., 2005) 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.

The work discussed in this paper combines both approaches to model the ambiguity

3 AMBI^{2}ONT ONTOLOGY

One of the problems we encountered modelling context data in previous projects was the use of the uncertainty and vagueness of the gathered information. In the Smartlab project (Almeida et al., 2009) 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 (Almeida et al., 2011) 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. The main elements of the ontology are: 1) *Location:* The subclasses of this class represent the location concepts of the context. 2) *LocableThing:* The subclasses of this class represent the elements of the system that have a physical location. 3) *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. 4) *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. 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 27ºC with a certainty factor of 0.2 and 18ºC with a certainty factor of 0.8” means that the value of the temperature is more probably 18ºC (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. Each ContextData individual has the following properties: 1) Crisp_value: the measure taken by the associated sensor. In our system a sensor is defined as anything that provides context information. 2) 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. 3) Linguistic_term: each measure has its fuzzy representation, represented as the linguistic term name and the membership degree for that term.

4 AMBIGUOUS SEMANTIC CONTEXT

The semantic context management is done in four steps: 1) add the measures to the ontology, 2) process the semantic and positional information, 3) apply the data fusion mechanism and 4) process the ambiguity contained in the data.

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 -10ºC and 50ºC 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, it is provided with each measure.

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 and the OWL Model. 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).

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 behaviours as stated in (Bloch, 1996): 1) Severe, the worst certainty factor from all the input measures is assigned to the combined measure; 2)Indulgent, the best certainty factor from all the input measures is assigned to the combined measure; 3)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* is the measure values and *cf* is the measure certainty factor. Finally we process 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 Open Source fuzzy reasoner to accept also uncertainty information. JFuzzyLogic follows the FCL 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. 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. 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 (Orchard, 1998). 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 *CFc* is the certainty factor of the consequent, *CFr* is the certainty factor of the rule and *CFf* is 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:

$$S = P(F_\alpha | F'_\alpha) \qquad if\ N(F_\alpha | F'_\alpha)$$

$$S = (N(F_\alpha|F'_\alpha) - 0.5) \times P(F_\alpha|F'_\alpha) \quad otherwise \qquad (4)$$

Where:

$$P(F_\alpha|F'_\alpha) = \max\left(\min\left(\mu_{F_\alpha}(u), \mu_{F'_\alpha}(u)\right)\right), \qquad \forall u \in U \qquad (5)$$

And:

$$N(F_\alpha|F'_\alpha) = 1 - P(\overline{F}_\alpha|F'_\alpha) \qquad (6)$$

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.

5 CONCLUSIONS AND FUTURE WORK

We have presented in this paper a context-aware system that takes into account the uncertainty and vagueness present in smart environments. We have also described an ontology to model this ambiguity. The presented system provides a more detailed picture of the environment, allowing a richer reasoning over the context. 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. Our final goal is to provide a more robust and flexible mechanism to manage the context, that allows capturing richer nuances of the environment.

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.

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