Quality Extensions and Uncertainty Handling for Context Ontologies

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Abstract. Context, by nature, involves real world entities and is therefore subject to uncertainty and inaccuracies. Ontologies are often used to model context in a formal way in order to achieve a shared semantic understanding of concepts and the relationships that hold among them. However, they lack support for representing ambiguous context and appropriate comparison algorithms. As such, context-aware applications may make the assumption that the context they use is completely accurate. In this paper we propose a simple and lightweight yet generic approach to extend context ontologies with quality of context properties and discuss the use of these quality properties for context ontology matching under uncertainty using fuzzy set theory. We illustrate the proposed extensions and uncertainty mechanisms with a small example where uncertain spatio-temporal coverage is combined with other contextual properties.

1 INTRODUCTION

Context-awareness has been drawing much attention from researchers in the ubiquitous and pervasive computing domain [12] as context has become a key ingredient to create a whole range of smart entertainment and business applications that are more supportive to the user. Context [4] has been defined as any information that can be used to characterize the situation of an entity. Humans take this context information into account rather intuitively, whereas context-aware applications require an explicit model to take advantage of context information for non-intrusive decision making and adaptation [9]. Imperfections in the context data can cause incorrect or unintended application behavior as relationships between similar context properties become uncertain. For example, the precision of a coordinate based positioning system is required to decide whether a given position matches with a location such as *'at the office'*.

In this paper we propose to extend context ontologies with quality of context properties and discuss a lightweight and generic approach for matching under uncertainty that is simple enough to be implemented and used on resource constrained devices, such as PDAs. The remainder of this paper is organized as follows. In section 2 we describe related work on quality of context and reasoning with uncertainty. Section 3 discusses how quality of context aspects are introduced into our context ontology. Section 4 describes the use of membership functions based on the concept of fuzzy set theory to achieve advanced matching mechanisms for context ontologies in the presence of uncertainty. In section 5 we conduct an experiment illustrating uncertain spatio-temporal coverage combined with other contextual properties to validate the matching mechanisms in more advanced scenarios. We conclude with section 6.

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2 RELATED WORK

In this section we focus on those contributions on quality of context and uncertainty management for mediation of ambiguous context that are most related to the work presented in this paper. This work is based on the ideas presented in Buchholz *et al.* [11], where the authors identify parameters that quantify the Quality of Context (QoC) and the inevitable uncertainty of sensed values for individual context properties:

- *Precision:* describes how sharply defined a measurement is stated and what the difference is with the actual value in the real world.
- *Probability of correctness:* estimates how often the context information is unintentionally wrong due to internal errors.
- *Trust-worthiness:* describes the reliability of the entity that may have persistently provided incorrect information in the past.
- *Resolution:* describes the granularity of the information and the inability to offer information with a finer detail.
- *Up-to-dateness:* describes the age of information which can be used to decide on the temporal relevancy in a particular situation.

Henricksen *et al.* [6] explore the problem of imperfect context information and characterize the following four types and sources of imperfect context information: *Unknown*, *Ambiguous*, *Imprecise* and *Erroneous*. The first two types of imperfection are new, whereas the latter two types combine several Quality of Context properties on the list of the work by Buchholz *et al.*.

In [7] Parsons describes qualitative methods for reasoning with various types of imperfect information and argues that qualitative methods have the advantage to not require precise numerical information, but instead to rely on abstractions such as interval values and information about how values change.

Chalmers *et al.* show in [1] how context can be formulated in the presence of uncertainty using interval arithmetic for numerical context values, and analogously using trees with abstract values for context ontologies. The authors define *within* and *overlap* relationships between actors and context objects both for numerical and abstract values in order to compare context information.

3 EXTENDING ONTOLOGIES WITH QUALITY PARAMETERS

Ontologies and the Web Ontology Language (OWL) are very popular for a systematic arrangement of context concepts and the relationships that hold among them [10, 2, 5]. In our previous work [3] we defined an OWL context model specifying *User*, *Platform*, *Service*, *Environment* and related concepts to provide a shared semantic understanding for context-driven adaptation of mobile services. Our context system [8] is able to gather and interpret this information. In

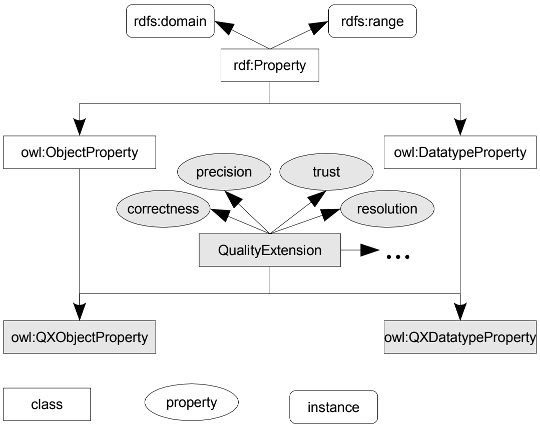

Figure 1. Extending the OWL language with QoC properties

the case of uncertainty in the gathered information, the context-aware system needs context quality parameters in OWL in order to determine a high confidence of correctness of matching context information. We will now show how the Quality of Context (QoC) parameters discussed in [11] are modeled by means of two new property types, *QXObjectProperty* and *QXDatatypeProperty*. Both property types inherit from the *DatatypeProperty* and *ObjectProperty* OWL language constructs, as well as from a self-defined class *QualityExtension* which models the Quality of Context parameters *precision, correctness, trust* and *resolution* as *DatatypeProperties*:

```
<owl:Class rdf:ID="QualityExtension" />

<owl:DatatypeProperty rdf:about="#precision">
  <rdfs:domain rdf:resource="#QualityExtension" />
  <rdfs:range rdf:resource="&xsd;#int" />
</owl:DatatypeProperty>
<owl:DatatypeProperty rdf:about="#correctness">
  <rdfs:domain rdf:resource="#QualityExtension" />
  <rdfs:range rdf:resource="&xsd;#int" />
</owl:DatatypeProperty>
...

<owl:Class rdf:ID="QXDatatypeProperty">
  <rdfs:subClassOf rdf:resource="&owl;#DatatypeProperty" />
  <rdfs:subClassOf rdf:resource="&owl;#QualityExtension" />
</owl:Class>
<owl:Class rdf:ID="QXObjectProperty">
  <rdfs:subClassOf rdf:resource="&owl;#ObjectProperty" />
  <rdfs:subClassOf rdf:resource="&owl;#QualityExtension" />
</owl:Class>
```

See Figure 1 for an overview of the property inheritance hierarchy. The QoC parameters of e.g. a sensor that instantiates the temperature concept in our context ontology [3] are modeled as follows:

```
<owl:Class rdf:ID="Sensor" />

<qx:QXDatatypeProperty rdf:about="#hasTemperature">
  <rdfs:domain rdf:resource="#Sensor" />
  <rdfs:range rdf:resource="&xsd;#int" />
  <qx:precision>95</qx:precision>
  <qx:correctness>100</qx:correctness>
  <qx:resolution>1</qx:resolution>
  ...
</qx:QXDatatypeProperty>
```

4 MATCHING IN THE PRESENCE OF UNCERTAINTY WITH FUZZY SETS

In the real world context information can be vague, imprecise, uncertain, ambiguous, inexact, or probabilistic in nature. We therefore

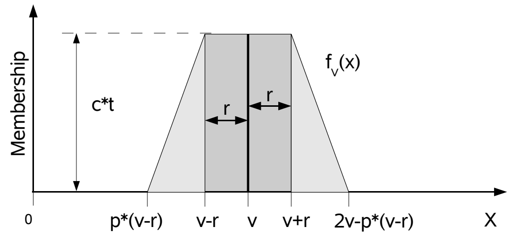

Figure 2. Membership function for a single sensed value with given Quality of Context parameters

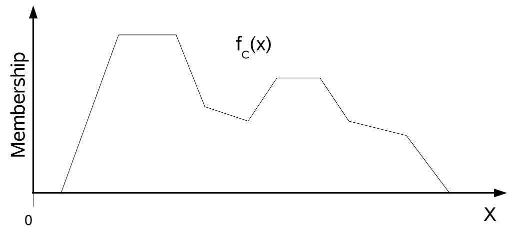

Figure 3. A fuzzy set C as a averaged sum of single fuzzy sets

need appropriate matching algorithms that take into account the imperfect nature of context when taking appropriate actions. In this section, we will show how we use concepts of fuzzy set theory of Zadeh [13] and define membership functions based on the quality of context parameters defined in the previous section.

4.1 Modeling a fuzzy context concept

In classical set theory the membership of an element to a set can be clearly described. In fuzzy set theory, an element belongs to a set with a certain possibility of membership. Age is a typical example of a fuzzy concept. There is no single quantitative value or clear boundary defined for the term *young*: age 25 can be young for some, while age 30 can be young for others. However, age 1 is definitely young, while age 100 is is definitely not young.

We can model the membership function for a single sensed value using the Quality of Context parameters in a similar way. Assume a sensed value v has a precision p, a probability of correctness c, a trust-worthiness t and a resolution r, with $0 \leq p, c, t \leq 1$, then we define the following symmetric membership function $f_V(x)$ with $x \in X$ for the sensed value v as in Figure 2. Note how the Quality of Context parameters change the crisp sensed value into an interval with a particular symmetric shape of the fuzzy set.

4.2 Aggregation and matching of fuzzy concepts

If a contextual concept C is defined by set of N measured values v_i then we can improve the accuracy of its membership function by using the aggregated membership of this concept $f_C(x)$ with $x \in X$ defined as the averaged sum of $f_{V_i}(x)$:

$$f_C(x) = \frac{\sum f_{V_i}(x)}{N} \qquad with \quad x \in X$$

For example, our WiFi location sensor uses multiple *Received Signal Strength Indication* (RSSI) values as a distance measurement to known access points and models them as fuzzy sets. An example of such an averaged sum of these fuzzy sets is shown in Figure 3. Note that the aggregated fuzzy set is no longer symmetric.

We define a match between two sensed values with fuzzy sets A and B and membership functions $f_A(x)$ and $f_B(x)$ based on the intersection of fuzzy sets A and B. The intersection [13] is a fuzzy set $C = A \bigcap B$ with a membership function $f_C(x) = f_A(x) \bigwedge f_B(x)$ which is defined as follows:

$$f_C(x) = f_A(x) \bigwedge f_B(x) = \text{Min}[f_A(x),\, f_B(x)]$$

Two fuzzy concepts match if their overlapping area is larger than a user-defined and context-specific threshold α:

$$0 \leq \alpha \leq \frac{\int_X f_C(x)}{Min[\int_X f_A(x), \int_X f_B(x)]} \leq 1 \qquad with \quad x \in X$$

Of course, when one of the membership functions is $f(x) = 0$ or when the overlap is zero, then there is no need to calculate this ratio.

5 EVALUATION

This subsection discusses the scenario used for a preliminary evaluation of the uncertainty mechanisms for matching context information. A PDA enabled with WiFi networking is used for *Received Signal Strength Indication* (RSSI) based location-awareness. The computer science building has about 100 offices, labs and meeting rooms and is equipped with 7 access points for wireless Internet access on all 5 floors. In the first step we trained the system by walking around in the building and taking about 10 measurements for several offices.

We determined the Quality of Context parameters based on a long test run while remaining at the same location. We looked for outliers in the sampled data, calculated the mean and variation in the data and estimated the values of the QoC parameters as follows:

- Precision: 95%
- Probability of correctness: 90%
- Trust-worthiness: 100%
- Resolution: 3 dBm

Using this information, the average fuzzy set for each of the access points that were seen in a particular office was calculated. After ordering the overlap ratios by decreasing order, and selecting the fuzzy set with the highest overlapping ratio, the locations matched, although non of the new RSSI measurements was exactly equal to a previously encountered measurement at the same location.

In a second test scenario which illustrates spatio-temporal coverage, my PDA informs the instant messaging client on my desktop system on my whereabouts and adjusts my status accordingly. I usually have lunch around 12h30 and 13h00 together with my colleagues in a room which is also used for meetings. Both time and place should match in order for my client to change to the *'out for lunch'* status. If only the location matches, then my status should be *'in a meeting'*. Otherwise, if I am not in my office, I will *'be right back'*. Both location and time are modeled as fuzzy sets.

This simple test case with multiple fuzzy sets being matched worked fine in 4 out of 5 cases. On one day I had lunch at 13h30, but had a meeting before at the same place. The instant messaging client decided too early that I was out for lunch, and claimed that I had a meeting while I was still having lunch. This was due to the fact that the precision for the lunch time was set to high in order to match.

In the end, this simple approach using fuzzy set matching worked rather well for this particular application. However, for a large number of fuzzy sets that have to match at the same time, it becomes very difficult to decide which context information matches best as more and more scenarios will become equally likely.

6 CONCLUSION

In this paper we have proposed a simple and lightweight extension to the OWL language to model quality of context properties in order to deal with ambiguous and imperfect context information. We have discussed the use of these quality parameters in automated uncertainty reasoning to achieve more advanced matching mechanisms for context ontologies. This automated uncertainty reasoning was based on concepts of fuzzy set theory. We have illustrated the proposed ontology extensions and the fuzzy comparing algorithms with small examples which included spatio-temporal coverage as fuzzy sets.

The proposed matching mechanisms are still a work in progress, but worked as expected for the examples. Difficulties are assumed to arise when the number of fuzzy sets involved in a single contextual condition is going to increase. We therefore will further continue to refine the membership functions by including the likelihood of context information in order to reduce to possible scenarios that may match under particular circumstances. One improvement that may proof to be useful is the inclusion of likelihood of events. This will better differentiate the likelihood of fuzzy matches.

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