Utilizing a Hierarchical Method to Deal with Uncertainty in Context-aware Systems

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Abstract. In context-aware systems, one of the main challenges is how to model context uncertainty well, since perceived context always yields uncertainty and ambiguity with consequential effect on the performance of context-aware system. To handle uncertainty in context-aware systems, firstly, we should know from where uncertainty comes. In this paper, we argue that uncertainty comes from several sources for each context level in context-aware systems. Based on this argument, we propose a hierarchical method to deal with context uncertainty in different levels, with the aim of reducing uncertainty and, developing a pattern to better understand this uncertainty. This will, in turn, helps in improving the system's reliability.

1 Introduction

Context plays an important role in ubiquitous computing systems. A lot of work has been done in trying to develop applications in ubiquitous computing environments context aware [1] [2] [3] [4] [5] [6].

One of the main challenges in context-aware systems is how to tackle context uncertainty well, since perceived context always yields uncertainty and ambiguity with consequential effect on the performance of context-aware systems [7] [8]. To handle context uncertainty well, first, we need to get the knowledge about the origins of uncertainty.

Fig. 1 shows typical information flow in a context-aware ubiquitous system. In this architecture, we argue that information flow from lower level to higher level will inevitably generate uncertainty so that we should analyze it in different phases:

- Phase 1: Raw sensor data to low-level context (S-LC)

The main factor that promotes uncertainty in S-LC is the often inherent inaccuracy and unreliability of many types of low-level sensors, which may lead to contradicting or substantially different reasoning about low-level context. In this phase, we propose to apply Dempster-Shafer Evidence Theory to handle uncertainty.

- Phase 2: Low-level context to high-level context (LC-HC)

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This phase is always referred to “Context Aggregator” or “Context Synthesizer”. In this phase, reasoning is always in the uncertain conditions. In this regard, we propose to use Bayesian Networks to infer high-level context.

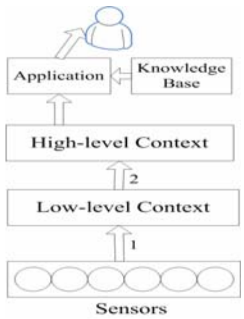

Fig. 1. Information flow in context-aware systems

2 S-LC Uncertainty

Sensor’s inherent uncertainty is the main source of this phase’s uncertainty. To handle this problem, sensor redundancy is usually applied. Sensor redundancy could improve system’s reliability, however, at the same time, it always generates sensor competition problem [9]. Sensor competition means the results of sensors representing the same measurement are competitive. Let us consider the following scenario:

The sensors here are three RFIDs (A, B and C). The output of each RFID is a Boolean variable (true or false). True means a user (Bob) is in room, while, false means it isn’t. Suppose the three RFIDs’ outputs are different. Two RFIDs shows that Bob is room, while, another one shows Bob is not in room. This is a typical sensor competition problem. In the following part, we will describe how to solve it.

The authors in [10] propose to use high-level and other same-level context to deal with this problem. However, we argue that it is not always useful. If high-level or same-level context is not available, this method can not work well. In this paper, we propose to use mathematical method to solve it.

2.1 Dumpster-Shafer Theory

The advantage of Dempster-Shafer theory is that it can work well even in the case of lack of knowledge of the complete probabilistic model required for other methods such as Bayesian inference. The Dempster-Shafer theory of evidence represents uncertainty in the form of belief functions. It is based on two ideas: the idea of obtaining degrees of belief for one question from subjective probabilities for a related question, and Dempster's rule for combining such degrees of belief when they are based on independent items of evidence [11].

Dempster-Shafer theory starts by assuming a universe of discourse, also called a frame of discernment, which is a set of mutually exclusive alternatives (similar to a state space in probability), denoted by Ω. Any hypothesis A will refer to a subset of Ω for which observers can present evidence. The set of all possible subsets of Ω, including itself and the null set $\varnothing$, is called a power set and designated as 2^{Ω}. Thus, the power set consists of all possible hypothesis 2^{Ω} ={ A_1, Ω, A_n }.

We can assign hypothesis to any of the three types of values. Basic probability numbers are a mapping of each hypothesis A to a value m(A) between 0 and 1, such that

- the basic probability number of the null set $\varnothing$ is $m(\varnothing)$ =0, and
- the sum $m(A_1)$ + … + $m(A_n)$ =1.

The second type of assignment is a belief function that maps each hypothesis B to a value bel(B), between 0 and 1, define as

$$bel(B) = \sum_{j:A_j \subset B} m(A_j). \tag{1}$$

The belief function represents the weight of evidence supporting B's provability.

The third type of assignment is a plausibility function that maps each hypothesis B to a value pls(B) between 0 and 1, defined as

$$pls(B) = \sum_{j:A_j \cap B \neq \varnothing} m(A_j). \tag{2}$$

The plausibility function is the weight of evidence that doesn't refute B, and belief and plausibility are related by

$$pls(B) = 1 - bel(\overline{B}), \tag{3}$$

Where $\overline{B}$ is the hypothesis "not B". Shafer showed that a one-to-one correspondence exists between basic probability numbers, belief, and plausibility, meaning that any of the three functions is sufficient for deriving the other two.

Dempster's Rule for combination is a procedure for combining independent pieces of evidence. Suppose $m_1(A)$ and $m_2(A)$ are the basic probability numbers from two independent observers. Dempster's rule for combination consists of the orthogonal sum

$$m(B) = m_1(B) \oplus m_2(B) = \frac{\sum_{i,j:A_i \cap A_j = B} m_1(A_i)m_2(A_j)}{\sum_{i,j:A_i \cap A_j = \varnothing} m_1(A_i)m_2(A_j)}. \tag{4}$$

We can combine more than two belief functions pairwise in any order.

2.2 Using Dempster-Shafer theory in our scenario

In our scenario, $\Omega = \{T, \overline{T}\}$, where T means Bob is in room, and $\overline{T}$ is the compliment event meaning Bob is not in the room. For this Ω, the power set has three elements: hypothesis H={T} that Bob is in room; hypothesis H={$\overline{T}$} that Bob is not; and hypothesis U=Ω that Bob is in room or not. Suppose the probability of RFID A being trustworthy is α. If RFID A claims that Bob is in room, then its basic probability assignment will be

$$m_1(H) = \alpha \qquad m_1(\overline{H}) = 0 \qquad m_1(U) = 1 - \alpha \tag{5}$$

If RFID A claims that Bob in not in room, its basic probability assignment will be

$$m_1(H) = 0 \;\; m_1(\overline{H}) = \alpha \;\; m_1(U) = 1 - \alpha \tag{6}$$

Likewise, given prior probabilities for the trustworthiness of RFID B and C, we would construct their basic probability assignments m_2 and m_3 similarly.

Next, the combined belief of A, B, and C in H is

$$bel(H) = m(H) = m_1(H) \oplus m_2(H) \oplus m_3(H)$$

Following Dempster's rule for combination (Equation 4), We can compute this by combining any pair of arguments and then combining the result with the remaining third argument. For example, let's first combine m_1 and m_2:

$$m_1(H) \oplus m_2(H) = \frac{1}{K}[m_1(H)m_2(H) + m_1(H)m_2(U) + m_1(U)m_2(H)]$$

$$m_1(\overline{H}) \oplus m_2(\overline{H}) = \frac{1}{K}[m_1(\overline{H})m_2(\overline{H}) + m_1(\overline{H})m_2(U) + m_1(U)m_2(\overline{H})]$$

$$m_1(U) \oplus m_2(U) = \frac{1}{K} m_1(U)m_2(U) \tag{7}$$

Where

$$\begin{aligned} K = {} & m_1(H)m_2(H) + m_1(H)m_2(U) + m_1(U)m_2(H) + \\ & m_1(\overline{H})m_2(\overline{H}) + m_1(\overline{H})m_2(U) + m_1(U)m_2(\overline{H}) + m_1(U)m_2(U) \end{aligned} \tag{8}$$

We can similarly combine the result from Equation 7 with m_3.

To use Dempster-Shafer theory, A, B and C's reliability must be known. We calculate initial reliability of each sensor by keeping a malcount for each of them and then comparing the malcounts to a set of thresholds; a malcount exceeding higher thresholds lowers the sensor's reliability rating.

3 LC-HC Uncertainty

In our paper, we propose to use Bayesian networks. Bayesian networks are a powerful way of handling uncertainty in reasoning. A Bayesian network is a directed acyclic graph of nodes. Nodes represent variables and arcs representing dependence relations among variables. For example, if there is an arc from node A to another node B, then A is a parent of B. In Bayesian networks, for each node, the conditional probability on its parent-set is stored. These locally stored probabilities can be combined using the chain rule [12] to construct the overall joint probability distribution *P*.

Two main merits of Bayesian networks drive us to adopt it.

One is that Bayesian networks can handle incomplete data sets. This point is very important as context-aware system is always partially-observable. The other one is that using Bayesian networks, we can learn causal relationships between low-level context and high-level context. So if only one or two kinds of low-level are available, we can select the most important one by causal relationships so as to improve reasoning accuracy.

Let’s see an example of Bayesian network. Considering the case in which the system needs to infer whether the user is having lunch or not. For inferring such an activity it is needed that we have some data about the location of the user, time of the day, and some data about his actions.. Through prior knowledge, we may construct a Bayesian network shown in Fig. 2. Then activity can be deduced from this network.

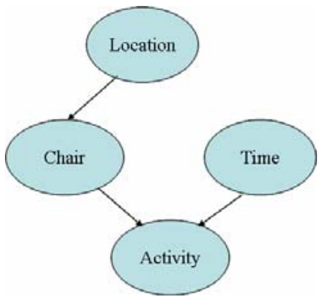

Fig.2. Bayesian network for activity reasoning

4 Conclusions and Future Work

In this paper, we propose a hierarchical method to deal with uncertainty in context-aware systems. Two different methods: Dempster-Shafer Theory and Bayesian Networks are applied in two different phases in our paper. We argue that this hierarchical method is feasible from the viewpoint of mathematical model. However, when using mathematical methods in real applications, many other aspects, such as hardware feasibility, time delay etc. should also be considered. The involve matter of these aspects in our current model is a topic of our future research. We are currently studying the application of different approaches on our test bed—CAMUS [13] and comparing their performance.

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