Context Awareness for a Smart Environment Utilizing Context Maps and Dempster-Shafer Theory

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Abstract. In this paper we describe context awareness for a smart home using previously collected qualitative data. Based on this, context experts estimate to what extent a behavior is likely to occur in the given situation. The experts' estimations are then combined using Dempster-Shafer Theory. The result can be used to (a) predict the most likely behavior and (b) to verify to what extent a behavior that has been detected is usual in the given situation.

Keywords: Smart Homes, Context Awareness, Dempster-Shafer Theory.

1 Motivation

Instead of moving to a care giving facility, many elderly or cognitively impaired people prefer to stay in the comfort of their own home, which in many cases even has a positive effect on their ability to fulfill the activities of daily living [1]. To aid the person whenever necessary a smart home system firstly must recognize what its inhabitant is currently doing, often based on sensor readings e.g. [2-5]. Once the behavior is identified the question arises: To what degree is the behavior normal or abnormal with respect to the context of the situation, e.g. the weather being nice, her blood sugar level being low, etc?

In this paper we describe how Dempster-Shafer Theory (DST) [6-7] can be utilized to achieve context awareness for a smart home by calculating the degree of normality of a behavior in the context of the situation it appears in.

2 Utilizing Dempster-Shafter Theory for Context Awareness

Generally, what context information needs to be considered depends on the particular inhabitant, it is often manifold, and includes: daily, weekly, and monthly routines, health condition, etc. A *context variable* is a property of the environment that can be measured e.g. day of week, indoor temperature, and weather condition. We opt for an approach where no previous assumption about which context variable influences which behavior has to be made. Instead we collect all context variable values whenever a behavior occurs in so called *context maps*. Whenever a behavior takes place, all context maps for that behavior, make an entry in the appropriate field that corresponds to the current value of the context variable. Table 1 shows two context maps for the behavior of grocery shopping. We can, for example, see from the weather map that during the time the inhabitant was observed (in our simulated case we annotated the context for each behavior in 1000 cases) she went grocery shopping 270 times while it was raining, and never while it was snowing.

Table 1. Context maps for the behavior of going out for grocery shopping.

Grocery Shopping									
Weather Map					Blood Sugar Map				
Rainy	Cloudy	Sunny	Foggy	Snowy	Very low	Low	Normal	High	Very high
270	290	310	130	0	0	190	794	0	0

A *context expert* is the part of the smart home system that provides a basic probability assignment (bpa) [6] of its degree of belief to which extent each behavior or behavior combination is likely to occur given the state of the corresponding context variable and the previously collected data in the context maps. For this estimation, the weather expert only takes the context variable weather into account, whereas the blood sugar expert's bpa is solely based on the context variable blood sugar, and similarly for all other experts. Each expert sets the mass for the alternative that describes the most likely behavior or most likely group of behaviors to 1 whereas the mass for all other alternatives are set to 0.

We combine the different experts' bpa with DST [6-7] which has been proven to be useful for behavior recognition e.g. [4]. The specific way of Dempster's rule of combination to deal with highly conflicting evidence is often considered to be negative [9] and other theories have been developed to overcome these issues. One of them is Dezert-Smarandache Theory (DSmT) that also has been used for activity recognition within a home-based care project [5]. However, in our case, we actually profit of Dempster's rule of combination in certain circumstances and will therefore use it in parallel to a different rule, mixing [10], that provides a simple weighted average of the evidence. Both theories together can handle the two different meanings that the basic probability number 0 can stand for (a) the expert can with certainty exclude the behavior (Dempster's rule) and (b) the behavior has never occurred in the given context but there is no reason to generally exclude it (mixing).

3 Results and Future Work

In order to implement and test our approach, we created a scenario of a fictive elderly person, Mary, who lives alone in a smart home [8]. The whole scenario has been simulated by Bayesian networks which create the context data for each behavior. Some of this data is collected in the context maps, as shown above. Other context information that is included in the simulation (e.g. the TV running) is on purpose left out to capture the problem that there are, in reality, more variables influencing an inhabitant's behavior than possibly can be observed in the smart home. To illustrate our results we will use a simple example with the finite domain of behaviors being: Θ = *{dishes, meal, grocery, none},* where *none* describes the case where no other behavior is possible.

After each context expert provided his bpa, Dempster's rule of combination and mixing are used in parallel to each provide an estimate to what degree each of the behaviors can be considered usual in the given context. Because of the way Dempster's rule deals with highly conflicting evidence, where a mass of 0 provided by one expert renders the behavior also in the combined result as abnormal, we can say that Dempster's rule provides its results solely based on information about which behaviors have been observed in the same context before. Mixing, on the contrary, provides information about what behaviors are principally allowed in the given context while still taking previously observed behaviors into account. The experts' bpa and the results of evidence combination for the three behaviors in the context of March, Saturday, 5am, normal blood sugar and sunny weather is shown in table 2.

Table 2. Experts' evidences (m_m m_d, m_h, m_b m_w), combined results for mixing (m_c, Bel_c, Pl_c) and combined results for Dempster's rule of combination (m_{DS}, Bel_{DS}, Pl_{DS}) for a given context.

Context: month = March, day = Saturday, hour = 5am, blood sugar = normal, weather = sunny										
	m_m	m_d	m_h	m_b	m_w	m_c	Bel_c	Pl_c	m_{DS}	Bel_{DS}	Pl_{DS}
{dishes}	0	0	0	0	0	0	0	0.8	0	0	0
{meal}	0	0	0	0	0	0	0	0.8	0	0	0
{grocery}	0	0	1	0	0	0.2	0.2	1	1	1	1
{dishes, meal}	0	0	0	0	0	0	0	0.8	0	0	0
{dishes, grocery}	0	0	0	0	0	0	0.2	1	0	1	1
{meal, grocery}	0	0	0	0	0	0	0.2	1	0	1	1
{dishes, meal ,grocery}	1	1	0	1	1	0.8	1	1	0	1	1
{none}	0	0	0	0	0	0	0	0	0	0	0

For the example calculations above we used a simple and intuitive function for each expert to assign its bpa. Whenever a behavior has been occurred in the context before an expert simply assigns mass = 1 for that behavior or behavior combination. It is, however, not necessary that each expert uses the same function. Expert functions could be customized to the type of information and/or the needs of the inhabitant. No matter what function an expert uses, its results can be translated into a bpa so that DST can be applied for combination and interpretation of the results. It will be interesting to investigate to what degree customized expert functions will improve the overall judgment of a behavior being normal or abnormal.

The usage of the very simple function applied in the example provides promising results. However, we hope to see more fine-tuned results when we will take the relative frequency of a behavior occurring in the context into account. A behavior that appears more frequent than another in the same context should probably be regarded as more usual than the other.

Because Dempster's rule is not scaling very well for huge amounts of data it will also be necessary to test our approach on a bigger scale, preferable with real smart home data to verify to what extent the approach can be used for context awareness in a real smart home environment and in real time.

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