Context Inference with Dynamic Component in the Ubiquitous Sensor Network

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Abstract. Dempster-Shafer Evidence Theory (DST) enables multi-sensor data fusion, which makes it possible to infer the context. Dempster-Shafer Evidence Theory provides good evidence to represent the uncertainty of the real world events. However, the previous researches focused on the inference to determine a particular situation or the cause of a specific situation. In this paper, we propose the way to infer the context in dynamic situations. It needs to designate critical focal elements and to check the *belief* in the applicable focal elements. The context inference in the dynamic situation becomes available, taking into account an occurrence of critical focal element events in a situation where critical focal element events are continued. This research can be applied to ubiquitous vehicles, small mobile objects, and helping the visually impaired persons to walk.

Keywords: Dempster-Shafer Evidence Theory, Context inference, Multi-sensor data fusion.

1 Introduction

The destinations of Ubiquitous Sensor Network (USN) are context awareness and individual service. We need the heterogeneous multi-sensor terminals and multi-sensor data fusion for the advanced context awareness in the USN: [1],[2]. For the context inference based on the multi-sensor data fusion, Dempster-Shafer Evidence Theory (DST) provides beneficial ways of reasoning: [4]. DST was, in fact, designed to stochastically represent the uncertainty of the real world. Nowadays, DST is a useful method of data fusion in the image processing and biometrics. Furthermore DST provides a profitable means of context inference: [3]. However, the existing ways of using DST are used to determine truth and falsehood of evidence. That is previous methods are used to infer the cause of a symptom that comes from a static situation: [4]. And the process is complex and the computation has to increase. In this paper, we propose the way to infer, combining the information from sensors based on the change patterns of the belief of focal elements, which will simplify the complex process in the existing calculation. This will contribute to prompt judgment and context inference on the dynamic situation. This paper is divided as shown below. In Chapter 2, the relevant studies are arranged. In Chapter 3, a novel context inference using multi-sensor data fusion is proposed. In Chapter 4, we present the experiments and evaluations. Finally in Chapter 5, the conclusion is made.

2 Previous Works

DST provides clues to the solution of problem in various fields. In an information security field, the accuracy of network intrusion detection was improved, fusing more than 2 complex factors rather than depending on a single factor: [11]. In a medical field, DST was used to improve the belief in diagnostic tests. There were some cases where the belief in diagnosis was improved by fusing the results, using multiple diagnostic test results rather than using a single test results in breast cancer screening: [10]. DST was used to infer the cause of context in emergency situations. To infer the causes, the belief in focal elements and uncertainty were compared and then the focal element with highest belief and the least uncertainty was inferred as decisive factor: [4]. As shown in these cases, context inferences using multi-sensor data fusion based on DST were accomplished in a static situation: [9].

3 Context inference with dynamic componets

There are static and dynamic conditions in the context of real world. Thus, we need prompt context inference even in the dynamic condition. We propose a novel way of context inference using DST to enable prompt inference in a dynamic condition.

3.1 Multi-sensor data fusion using DST

DST-based multi-sensor data fusion goes through the following process: [6],[7],[8].

For all evidence E_k: $\quad \text{Belief}_i(A) = \sum_{E_k \subseteq A} m_i(E_k)$ (1)

$$\text{Plausibility}_i(A) = 1 - \sum_{E_k \cap A = \phi} m_i(E_k) \tag{2}$$

Combining sensor S_i's observation m_i and sensor S_j's observation m_j:

$$(m_i \oplus m_j)(A) = \frac{\sum_{E_k \cap E_{k'} = A} m_i(E_k) m_j(E_{k'})}{1 - \sum_{E_k \cap E_{k'} = \phi} m_i(E_k) m_j(E_{k'})} \tag{3}$$

3.2 Context inference with dynamic componet

The methods for DST-based multi-sensor data fusion detecting dynamic situations and context inference are as follows;

1) Set focal elements

2) Compute Basic Probability Assignment
3) Compute belief and plausibility of focal element
4) Choose the focal element that has the highest belief and the lowest uncertainty

These steps are existing ways of context inference using DST: [12]. In this paper, we propose a novel context inference with dynamic component. A dynamic situation refers to an environment where the situations are variable and unstable. And the situation is related to the time. The methods for context inference in accordance with the time are as follows;

BPA of each focal element are calculated at time T1, and then its *belief*, *plausibility* and *uncertainty* are computed. At time T2, BPA is calculated again, and then its *belief*, *plausibility* and *uncertainty* are computed again.

After that, these computed ones are fused into one according to DST based multi-sensor data fusion method. Consequently, each context at time T1 and T2 can become merged. Here again, at time T3, its *belief*, *plausibility*, and *uncertainty* are computed, and then are merged with the merged result of T1 and T2. The data fusion formula is presented as follows.

$$m(T'_i) = \frac{\sum_{T_{i-1} \cap T_i \neq \emptyset} m(T_{i-1}) \cdot m(T_i)}{1 - \sum_{T_{i-1} \cap T_i = \emptyset} m(T_{i-1}) \cdot m(T_i)} \quad , i=1,2,3,\ldots,n \tag{4}$$

Here in the formula, $m(T_i)$ means the value of BPA function for sensed values of each sensor performing detection at an interval of 10 seconds. The current status' $m(T'_i)$ can be acquired through the data fusion of initial status' data and $m(T_{i-1})$. The initial status' BPA is $m(T_0)$. Provided that BPA of 10 seconds later is $m(T_1)$, $m(T'_1)$ is the fusion result of the initial status and the 10 seconds later one.

$$m(T'_1) = \frac{\sum_{T_0 \cap T_1 \neq \emptyset} m(T_0) \cdot m(T_1)}{1 - \sum_{T_0 \cap T_1 \neq \emptyset} m(T_0) \cdot m(T_1)} \tag{5}$$

Therefore, the result of 20 seconds later is as follows.

$$m(T'_2) = \frac{\sum_{T'_1 \cap T_2 \neq \emptyset} m(T_1) \cdot m(T_2)}{1 - \sum_{T'_1 \cap T_2 \neq \emptyset} m(T_1) \cdot m(T_2)} \tag{6}$$

Table 1. focal elements for inference of each time zone.

Initial status, $m(T_0)$	Focal elements	After 10 seconds, $m(T_1)$
$m(T_{01})$	h_1	$m(T_{11})$
$m(T_{02})$	h_2	$m(T_{12})$
$m(T_{03})$	h_3	$m(T_{13})$
$m(T_{04})$	$h_1 \cup h_2$	$m(T_{14})$
$m(T_{05})$	$h_1 \cup h_3$	$m(T_{15})$
$m(T_{06})$	$h_2 \cup h_3$	$m(T_{16})$
$m(T_{07})$	$h_1 \cup h_2 \cup h_3$	$m(T_{17})$

With these BPA, we can compute the belief, plausibility and uncertainty of focal element. And then comparing the belief and uncertainty is the last step to the context inference. We can find out the source of a trouble with comparing the belief and uncertainty of each focal element: [12].

In this paper, we propose a novel way of comparing the beliefs only. For knowing an object moving around ourselves, we adopt three kinds of sensor. And when we want to know whether it comes closer or not, we might as well check the belief of a focal element that made up of events from three kinds of sensor at time T_1, T_2, T_3.

At first, we have to compute the belief with the BPA of each focal element. And then we make search for the highest belief of all focal elements. We assume this focal element as a crucial focal element. We check the belief value in the next time T_2. We will do over again in the next time T_3. We want to know the object's moving is dangerous or not. The variation of belief shows what is meaningful moving because of the focal elements are a kind of substitute for cases that consist of events and the BPA is a reflection of relative importance of the focal element. Therefore, it can be the increasing belief of a focal element means the moving object comes closer. This assertion is rational under the condition that the BPA reflects relative importance among the context of real world. In the next chapter, we will verify this method through the experiments.

4 Experiment and Evaluation

Designating sensors to determine decisive factors is important in dynamic situation. This paper addresses reaching the information of the mobile objects and the situations include those mobile objects. The mobile objects generate sounds in engines, wheels, and rails; and the distance from the reference point varies in accordance with location transfer. Thus, the following sensors are needed to predict the contact or the impact between objects with sensors and other mobile objects; 1) a noise sensor, 2) an ultrasonic sensor to measure distance, and 3) an ultrasonic sensor to detect proximity in location. In addition to this, it needs to pay attention to the sensed information in a critical situation as follows. It needs to measure distance by using an ultrasonic sensor in a situation in which the emergence or the movement of mobile objects is expected. When those objects get closer, it needs to determine the proximity. At this time it is possible to determine the proximity by using an ultrasonic sensor for proximity. To do this, it needs to determine an increase of *belief* and an increase of *uncertainty* in $\{s_1\}$ after the events in focal element $\{s_1\}$, where $\{s_1\}$ is the default event for all events occurring. The next is to check the changes in time for the *belief* in ultrasonic sensing value $\{s_2\}$ measuring the distance from the objects with sensors. When the distance becomes remote, alert is relieved temporarily, yet the sensing activity of an ultrasonic sensor $\{s_3\}$ detecting proximity is not stopped. In case only $\{s_3\}$ reports the events where as $\{s_1\}$ does not incur events and $\{s_2\}$ does not report events, $\{s_1\}$ and $\{s_2\}$ need to sense the events again, which means a role of an ultrasonic sensor detecting the location of a mobile object in the proximity is critical. Thus, it needs to give weights to the sensed events. It needs to give weights to a case where the events keep increasing in a state of less noise. In addition, it needs to give weights to the events detected by an ultrasonic sensor determining proximity because it indicates the proximity of mobile objects. Based on this scenario, it is possible to constitute focal elements for the events sensed by each sensor as follows. Providing the BPA to each focal element is given by professionals. The *belief* of each focal element and *plausibility* can be calculated as shown in Table as below.

Table 2. Changes in *belief*

Focal element	bel(T'$_0$)	bel(T'$_1$)	bel(T'$_2$)	bel(T'$_3$)
Ω	1	1	1	1
$h_1 \cup h_2$	0.05	0.1	0.1047	0.3571
$h_1 \cup h_3$	0.4	0.4	0.6230	0.5417
$h_2 \cup h_3$	0.45	0.5	0.7120	0.7054
h_1	0	0.05	0.0445	0.0774
h_2	0	0	0.0262	0.1964
h_3	0.2	0.25	0.4634	0.3304

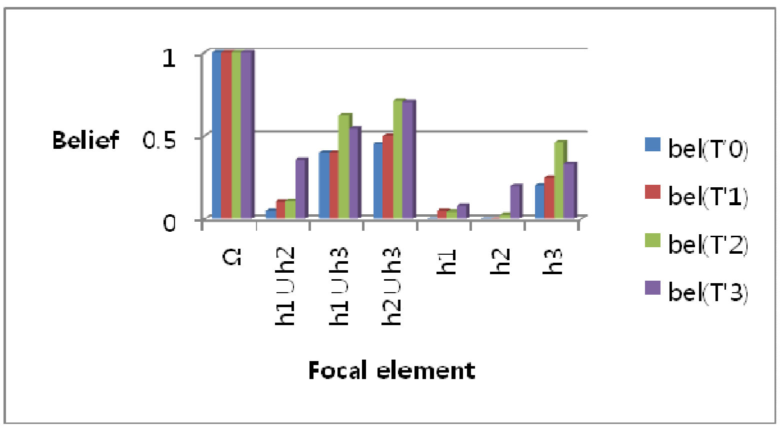

Fig. 1. Focal elements' *belief* in each time zone

At this time, if an event of $\{s_2\}$ where the distance gets closer in situation of increasing noise and when the distance keeps getting closer occurs, the operation of proximity sensor is instructed. When an ultrasonic sensor to determine the proximity, incurs events, the *belief* in focal elements $\{S_1, S_2, \text{and } S_3\}$ rapidly increases. At this time, we infer the approach of mobile objects and raise emergency warning

5. Conclusion.

DST-based multi-sensor data fusion and context inference using this model has been widely used to recognize static situations. However, we propose the ways to infer the situations with uncertainty in dynamic situations. It needs to designate basic focal elements and critical focal elements and to check the *belief* in the applicable focal elements. The context inference with uncertainty in a dynamic situation becomes available, taking into account an occurrence of critical focal element events in a situation where critical focal element events are continued. This research can be applied to Ubiquitous vehicles, small mobile objects, and helping the visually impaired persons to walk. The tasks for the future researches are anticipated to be developed to the context inference including even prior information as well as the situations without signal-based prior information.

Acknowledgements. Funding for this paper was provided by Namseoul University.

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