Multi-sensor Data Fusion with Dynamic Component for Context Awareness

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Abstract

Dempster-Shafer Evidence Theory(DST) enables multi-sensor data fusion, which makes it possible to infer the context. In this paper, we propose about how to use multi-sensor data fusion to infer context in the dynamic circumstances. Dynamic circumstance means a changing of the situation or the surrounding itself, and particularly signifies that there is a changeable factor in a specific environment. It is measures to recognize an expected situation of a moving object's approach, contact and collision in advance. While pre-existing context inference method using Dempster-Shafer evidence theory considered belief and uncertainty at the same time, in this paper, we propose the measures that focus on change of belief. Because in dynamic circumstances, It can be an alternative of no necessity of checking uncertainty that repetitive estimating of belief in the lapse of time. With this, we can apply to recognizing a situation that rapidly proceeds as time passes.

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

1. Introduction

The destinations of Ubiquitous Sensor Network (USN) are context awareness and personalization services. So far, important area of the USN research is securing energy efficiency. Because wireless sensor networks have a weakness that it have too short life to secure time to reach target because of energy consuming of sensor mote. Now, there is an upsurge of interest about the research of context awareness. 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 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].

Previous context awareness using multi-sensor data fusion is useful for inference of static situation. It has too many procedure of calculation. So it is disadvantageous for prompt context awareness. We need the multi-sensor data fusion method that can infer even in the dynamic situation. It also can infer in the situation that changes with time. We need the method; inferring the situation quickly, reducing calculations, producing results of calculations fast, can predict the situation. In this paper, to achieve this purpose, we propose a swift context inference method in a dynamic situation. Dynamic situation is that situations occur continuously. It requires careful observing in continuous change. When a noticeable big change happens, it requires swift detecting and decision on the situation. This paper proposes the method that infers situation on the basis of noticing the change of *belief* of each focal element to make prompt context inference using DST in a dynamic situation. Thereby, we confirm that it can apply to various cases need urgent decision. It can be a way that is able to infer that dynamic factors have what influence and importance about various situations that are made up by dynamic factors.

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

Multi-sensor data fusion researches are conducted in various fields. Multi-sensor data fusion can be performed by using four main ways; using Kalman Filter; using Baeysian Theory(including DST)'s probability theory; using Neural Network Theory; using Fuzzy Theory. Among the rest, the multi-sensor data fusion method using DST synthesized a disparate image of geography in geometrics and was used to extract improved geographic information. Image information of topography and buildings is able to acquire in various ways. It was used in clearing up information of topography and buildings by fusing different information of images. 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. Inferring the causes, the *belief* and the *uncertainty* in focal elements were compared and then the focal element with highest *belief*, the least *uncertainty* was inferred as a 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. Multi-sensor Data Fusion with Dynamic Components

There are static and dynamic conditions in the context of the real world. Static information is standardized and fixed information like a picture of topology and buildings taken from an airplane. Dynamic situation means the changing situation that overall surroundings or factors which constitute situation; or changing relations of situations among the objects which exists in the overall surroundings. We propose the method of predicting situation caused by changing and moving of objects which exists in limited space. It is inferring correlation with the criterion object, while sensing movements of other moving objects focusing on the criterion. In other words, it is the method that recognizes approach, contact and collision between a moving object and another object. As the object that we want to recognize is moving, it is important to recognize quickly based on obtained information. To recognize dynamic situation quickly, we use DST. We propose the method that reduces calculations, which is the weakness of the previous method of using DST, and infers situation quickly.

3.1 Multi-sensor data fusion using DST

It is BPA that is important in multi-sensor data fusion using DST. Finding or giving values of BPA, we can find belief and plausibility of focal element using BPA. It is as in the following.

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

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

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

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

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

We can perform a fusion of disparate values of signals using formula (3).

3.2Multi-sensor data fusion with dynamic component

Cause inference using DST is to compute the *belief* and the *plausibility* using BPA. Then, it finds the highest value of *belief* among each focal element. Among the focal elements which have high values of *belief*, it finds the lowest value of *uncertainty*. *Uncertainty* means that *belief* subtracted from *plausibility*. If we place pre-existing cause inference method using DST in order, it is as in the following.

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 previous way of context inference using DST [12]. In this paper, we propose a novel context inference with dynamic component. The situation is related to the time.

Dynamic context is showing change with time. So it is necessary that sensing of the situation at regular intervals and reporting transmitted sensing information to host through gateway. At this time, we should perform time-based data fusion of the relevant time about information obtained by various sensors and infer context of the relevant time. The BPA from each time slot is an important basis for calculating *belief* and *plausibility* of each focal element to infer context.

Following formula is the method of multi-sensor data fusion about BPA of heterogeneous sensor in each time slot. To perform context inference using DST in dynamic circumstance, it is important applying a change of BPA over time. BPAs of each time slot are calculated on the basis of sensing information of sensors. In this paper, it is out of discussion the process of calculating BPA. It is an important process in this study to find values of *belief* and *plausibility* of each focal element, applying DST based on BPA of each focal element in each time slot.

The data fusion formula is presented as follows.

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

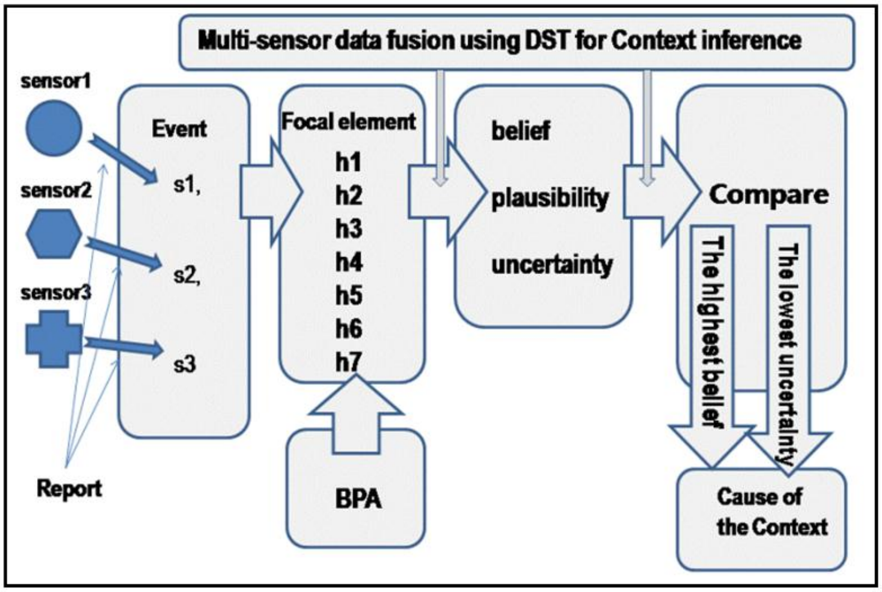

Figure 1. Multi-sensor Data Fusion using DST for Context Inference

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. Then comparing the *belief* and *uncertainty* is the last step to the context inference [12].

In this, *belief* means that if there is evidence, certain event "must" happen. In other words, there is an evidence, it is true that a certain event. In contrast, *plausibility* means the possibility that if there is a certain evidence, certain event "will" happen. *Uncertainty* means that *belief* subtracted from *plausibility*. This interval value means that a certain event can happen or not conditionally. In this study, we only take notice of *belief*. Because it is possible understanding the changing shape of a certain event by very estimating *belief* of occurring event as certain evidence appears. It is a matter of speed to decide the changing shape of a certain event in limited time. Allowing sufficient time to compute accuracy cannot be prior to "speed". Table 1 is BPAs of each focal element in the process of time slot. The focal elements of Table 1 mean an event or a situation by the evidence reported sensing information from 3 kinds of sensors.

As calculating *belief* and *plausibility* based on BPA from each time slot, we should take notice of focal elements, which have high value of *belief*. We also should remind that each focal element means the moving object's context of movement in dynamic circumstance. Focal elements have a description and meaning of a moving object's context of movement; we need to regard the focal element having highly valued *belief* as noticeable focal element. It is major items to be confirmed whether *belief* of this noticeable focal element increase at the next time slot.

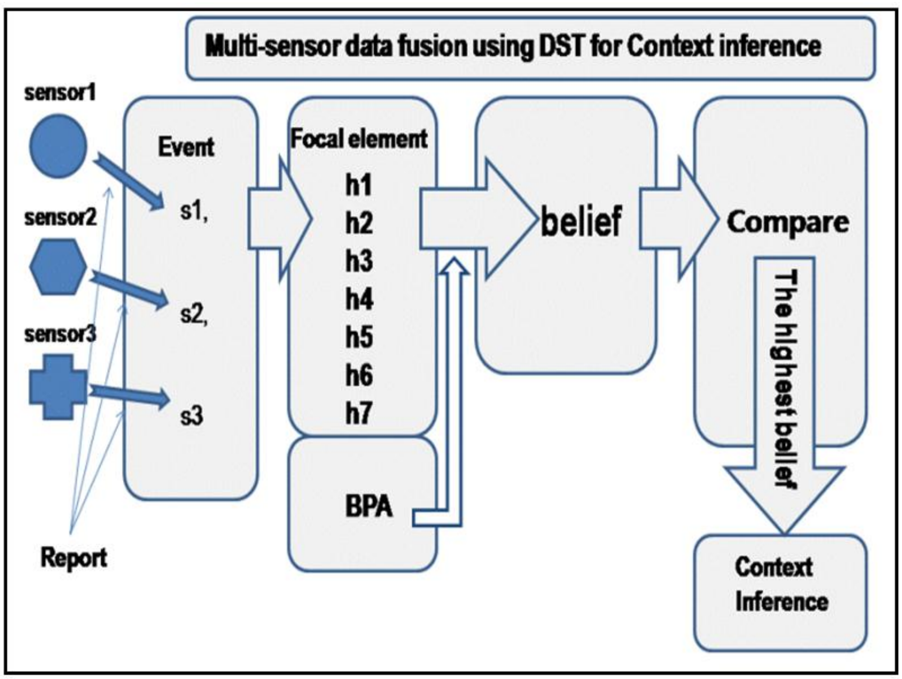

Figure 2. Multi-sensor Data Fusion using DST for Context Inference

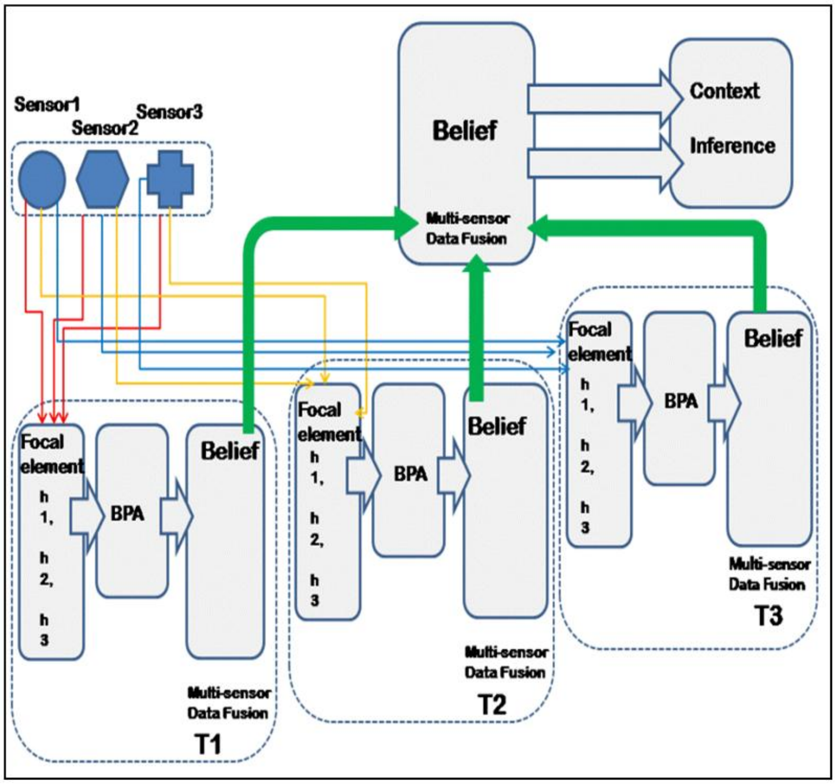

Figure 3. Modeling of Context Inference in the Dynamic Circumstance

4. Experiment and Evaluation

Designating sensors to determine crucial factors is important in a dynamic situation. At first, we have to compute the *belief* with the BPA of each focal element. 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 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 the relative importance among the context of real world.

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 variation of position. 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, we need 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 report 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 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 the 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

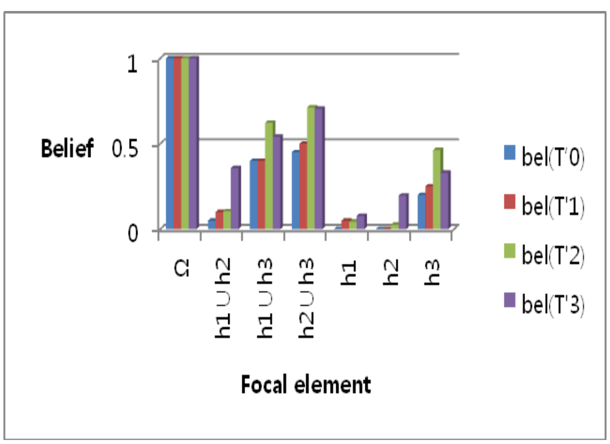

Figure 4. Focal Elements' *belief* in each Time Zone

At this time, if an event of s_2 where the distance gets closer in a 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, and S_3 rapidly increases. We infer the approach of mobile objects.

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 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.

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