Weight for Dynamic Context in the Wireless Sensor Network

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Abstract. Dempster-Shafer Evidence Theory (DST) plays an important role in multi-sensor data fusion. It needs to consider a number of wireless sensor network features when producing context information, collecting the information from wireless sensors. Understanding the important factors affecting context inference and weighing them adequately is essential. In this paper, we propose the ways to weight the focal element in multi-sensor data fusion. As for the criteria for weighing, the frequency of each sensor in the variable dynamic environment and the overlapping situation by time zone are considered. According to this, we can reach enhanced result of data fusion.

Keywords: Dempster-Shafer Evidence Theory, Multi-sensor data fusion, Wireless Sensor Networks, Weight.

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

With respect to weighting in wireless sensor network, Huadong Woo proposed weighting method based on the Kalman equation: [5]. Suh D.H. proposed event-frequency-based weights, calculating the weights depending on the event frequency reported by the sensors constructing wireless sensor network: [9]. And then he calculated relative frequency and absolute frequency and considered a case in which each frequency was taken into consideration and weight were not given. This study calculated the belief and the plausibility in each focal element, and the uncertainty, giving weights to the basic probability assignment (BPA) of each focal element depending on the event frequency reported by a sensor mote constructing a wireless sensor network: [4]. However, these previous studies are based on static situations. In other words, these studies did not take into account dynamic condition. Thus, it needs to develop the way to weight, taking into account the variable factors in a dynamic environment.

3 Way to weight in the dynamic situation

The context of real world is bound to be variable in most cases. In other words, situations are dynamic. Dynamic situation means situations change over time and this change pattern continues. In this case, sensors need to detect the situations when a specific amount of time elapses and sensors needs to fuse the collected information by each time slot. At this time, there are a few things to be considered during the repeated fusion. We propose the ways to weight in a dynamic condition as follows.
In general, real world's situations change over time. Wireless sensor networks sense every 10 seconds and report the sensed values to hosts through sink nodes, which means the sensed information are collected every 10 seconds and data fusion is conducted based upon this. Data fusion by each time zone is as follows: [10].

∑~~~~∩~~ø~~~~~~~~·~~~~~

~~T~ ~~ = ~~∑ ~~~~∩~~ø ~~~~~~~·~~~~~ $\qquad$ i==*1,2,3,...,n* $\qquad$ (1)

3.1 Calculation of weight

As shown in figure, the number of sensor motes reporting events by each sensor may vary depending on the sensor type. In this circumstance, weighting by taking into account the number of events make significance. However, in a dynamic situation, the event frequency reported first can be different from that reported after 10 seconds. In this case, what is to be added to weights? It is the iterated event frequency. If the sensor motes which incurred the first event still incur events after 10 seconds, it needs to check the number of sensor motes detecting and reporting events repeatedly and to introduce the findings to calculating the weights by each sensor.

t : event, f: frequency of events, we can express the weight as follows,

$$w = tf \quad (2)$$

We will consider another weight based on the repetition of the events of sensors.
repetition events of S1 at T1 and T2 : ∑ ~~ f~~~~
repetition events of S2 at T1 and T2 : ∑ ~~ f~~~~
repetition events of S3 at T1 and T2 : ∑ ~~ f~~~~
repetition events of sensors at time interval : ∑ ~~∪~~··· ∪~~ f~~~~~~

So, another weight *w*2 is ; *w*2 = ∑"~∪"#··· ∪"$ ~ ~ !~ / ∑ ~~∪~~··· ∪~~ (3)

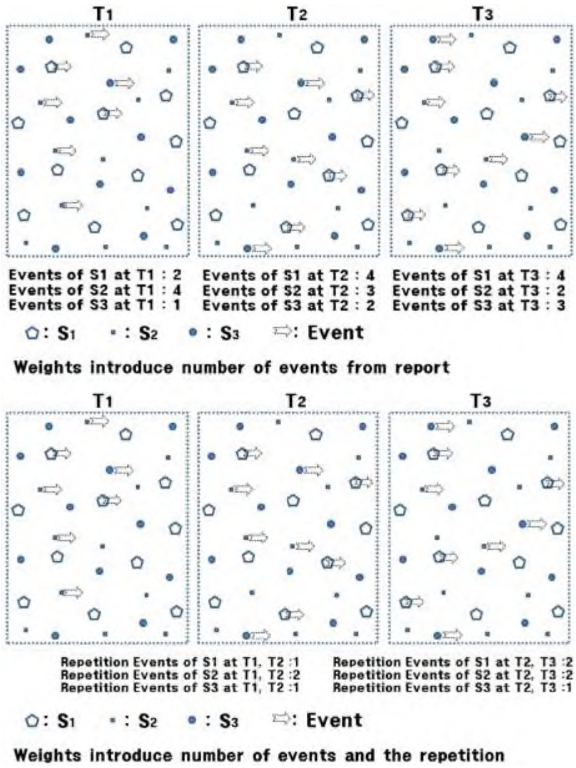

Fig. 1. Ways of weight in the wireless sensor networks; frequency of events and the repetition of events of sensors with the time lapse.

4 Experiment and Evaluation

As shown in the findings from the experiments, context inference becomes clearer when giving weights than before giving weights. And it can be said the weights calculated in a way proposed in this paper facilitates clearer context inference in real situations

Table 1. The BPA, *belief* and *plausibility* before weighting

Focal element	h_1	h_2	h_3	h_1Uh_2	h_1Uh_3	h_2Uh_3	Q	
	0.15	0.1	0.03	0.07	0.18	0.22	0.25	$m(A_t)$
T1	0.15	0.1	0.03	0.32	0.36	0.35	1	$bel(A_t)$
	0.65	0.64	0.68	0.97	0.9	0.85	1	$pl(A_t)$
	0.07	0.03	0.2	0.05	0.15	0.2	0.3	$m(B_t)$
T2	0.07	0.03	0.2	0.15	0.42	0.43	1	$bel(B_t)$
	0.57	0.58	0.85	0.8	0.97	0.93	1	$pl(B_t)$

Table 2. The *belief* and *plausibility* from the weighted BPA.

Focal element	h_1	h_2	h_3	h_1Uh_2	h_1Uh_3	h_2Uh_3	Q	
	0.057471	0.076628	0.011494	0.08046	0.137931	0.252874	0.383142	$m(A_t)$
T1	0.057471	0.076628	0.011494	0.214559	0.206897	0.340996	1	$bel(A_t)$
	0.659004	0.793103	0.785441	0.988506	0.923372	0.942529	1	$pl(A_t)$
	0.044444	0.019048	0.063492	0.063492	0.142857	0.190476	0.47619	$m(B_t)$
T2	0.044444	0.019048	0.063492	0.126984	0.250794	0.273016	1	$bel(B_t)$
	0.726984	0.749206	0.873016	0.936508	0.980952	0.955556	1	$pl(B_t)$

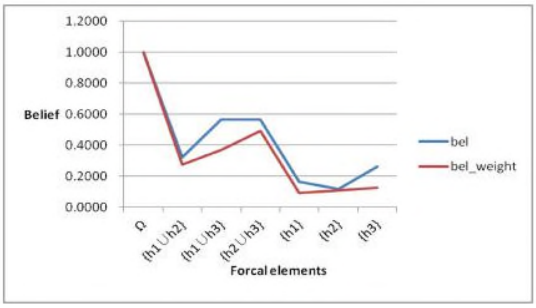

Fig. 2 The *belief* is change after weight the BPA, that is make in each time zone

5. Conclusion.

Weighting take into account the sensor networks' characteristics are needed for context inference. Sensor networks consist of a large number of sensor nodes and the sensor motes playing a role as terminal nodes consist of a large number of sensor motes. In addition to this, the context awareness using sensor networks aims to determine static situations in some cases, yet to estimate dynamic situation and sense and report by time zone in many cases. In this circumstance, taking into account the repetitive events reported by sensors according the change in time to calculate weight is very useful for context inference as shown in the experiments. The findings from this study are anticipated to be used in many other fields as well as the field relating to context awareness. The tasks of the future studies need to deal with the practical application of the findings in this paper and the advanced studies on more complex weights are anticipated.

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