A Novel Weighting Method for Context Inference

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Abstract

Dempster-Shafer Evidence Theory (DST) plays an important role in multi-sensor data fusion. In this paper, we propose weighting method based on event information sensor of aggregation for context awareness in wireless sensor networks. Context inference in wireless sensor networks has to use weighting method, and context inference based on sensor aggregation due to structure feature of wireless sensor network. We propose weight method based on event frequency of the sensor and the repetitive of event report sensor at the continuous time slot. The validity of reasoning through context inference in wireless sensor network can improve.

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

1. Introduction

Context of real-world includes very wide variety of factors, the respective influence of these factors in their situation and is configuration factors of the situation. Context awareness through the USN is still a lack of accuracy. We infer only context through USN. DST has been used as a good tool of context inference through the USN. We can multi-sensor data fusion through DST and more high-level context inference by using a heterogeneous sensor than use a single sensor. However, we must assign weights about heterogeneous sensor sensing information. In a previous study, the study of weighting method was not attended research on multi-sensor data fusion itself or the context awareness research in considering the structural properties of the USN. Therefore, in this paper, we propose a method to improve the reliability of context inference by assigning reasonable weights while multi-sensor fused data for context inference from the USN. The appropriate weighting method about collected information of sensors is contributed to decrease the uncertainty of context inference and will help that each sensor infer the situation closely.

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 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]. 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]. He has attempted context awareness using DST, calculated weights dynamic way with the Kalman filter for Weighting. 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]. 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]. In addition to proposed, to assign weights by evaluating ways if variety factors have contributed to the situation. It assigned weights the focus elements from calculate the weights of the multi-factors based Entropy analysis. 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. A Novel Weighting for Context Inference

The context of real world is bound to be variable in most cases. Context awareness is a very complex task. Because of the context awareness of real world take into account a variety of factors. It is difficult and very complex work that context inference using sensor in the remote. However, the goal of using USN is to provide very intelligent services, so that have to infer context based collecting information from sensor motes. The performance of the sensor plays an important more than to know exactly what the context in the real world. However, we consider the cost effectiveness because of the performance of the sensor cannot be increased indefinitely. To upgrade limited the ability of the sensor is necessary to employ different kinds of sensors in a wireless sensor network. We need multi-sensor data fusion to context inference using such a multi-sensor network system. We cannot be expected that all of the sensors have equal weight, the roles and function in each situation. It is a problem that provides information about applying uniform weights with context inference based on the sensing information. In this paper, we propose determine the weighting method in the process multi-sensor data fusion for context inference.

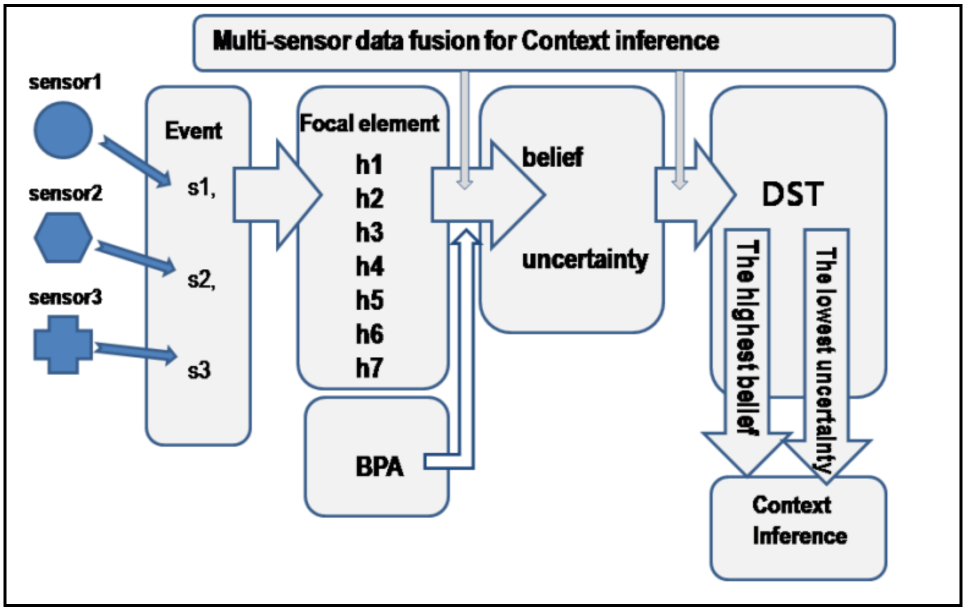


Figure 1. Multi-sensor Data Fusion using DST for Context Inference

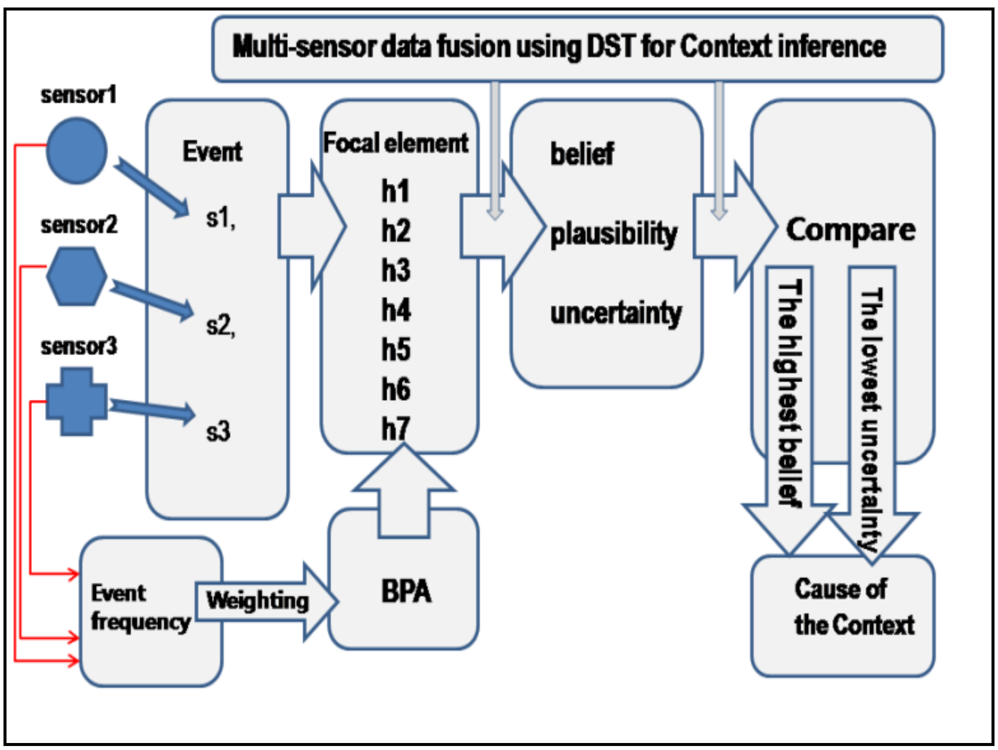


Figure 2. Multi-sensor Data Fusion using DST for Context Inference

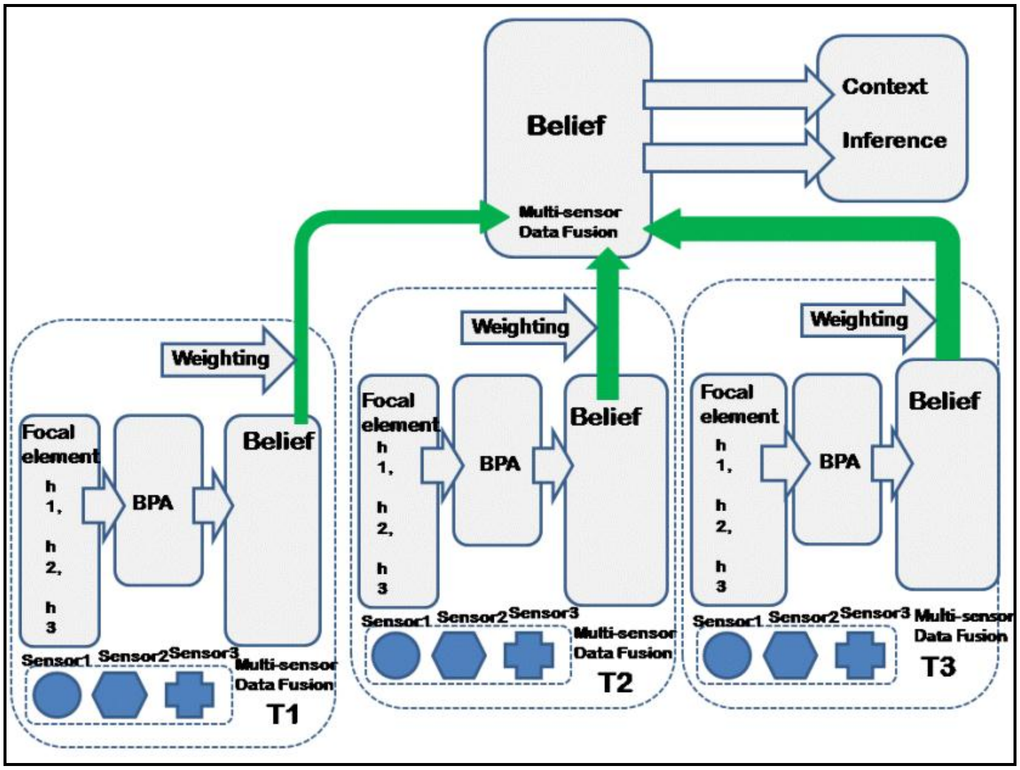


Figure 3. Modeling of Context Inference in the Dynamic Circumstance

We should be remembered that the wireless sensor network consisting of a large number of sensor motes. There is also events reported among the same type of sensor motes and is not reported. We will be able to have more confidence sensor that has the number of events reported on the sensing information from many sensors. For example, there are temperature sensors, humidity sensors, illumination sensors for monitoring forest fires in a wireless sensor network system. If 1000 sensor uniformly distributed in the same area, temperature sensors are reported 10 of 1000 sensor motes that event occurred and humidity sensors are reported 500 of 1000 sensor motes that event occurred. In this case, it is a problem that is calculated with equal weights. Therefore, we need weighting method based on events frequency in wireless sensor networks consist of a large number of heterogeneous sensors. In this paper, we propose a novel weighting method with considering the frequency of repeat events at the time interval, in addition to, previous weighting method based on events frequency. Sensors are uniformly distributed within a limited area can report repeatedly sensing information events along the shortest time interval or cannot report events. Then it means that assign weights to sensor nodes based on the number of events reported repeatedly at various time interval. The following formula is again sensed BPA at 10 second intervals and BPA of each fusion method at each time zone.

Wireless sensor networks survey 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].

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

3.1 Calculation of Weight

As shown in the 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. When a sensor which incurred the first event incur event after 10 seconds, it needs to check the number of sensor motes detect and report events repeatedly and introduce the findings to calculating the weights by each sensor.

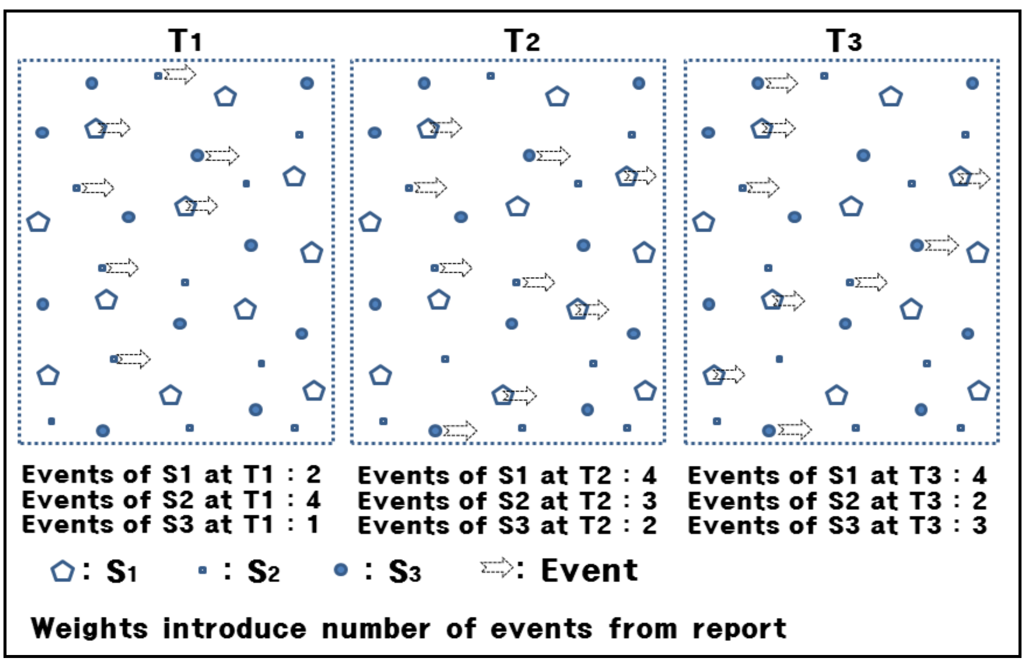
t : event, f : frequency of events, we can express the weight as follows,

$$w=tf \tag{2}$$

We will consider another weight based on the repetition of the events of sensors.

repetition events of S_1 at T1 and T2 : $\sum_{S1} f_{T1T2}$
repetition events of S_2 at T1 and T2 : $\sum_{S2} f_{T1T2}$
repetition events of S_3 at T1 and T2 : $\sum_{S3} f_{T1T2}$
repetition events of sensors at time interval : $\sum_{S1\cup S2\cdots\cup Sn} f_{TiTi+1}$

So, weight w_2 is ; $w_2 = \dfrac{\sum_{S1\cup S2\cdots\cup Sn} f_{TiTi+1}}{\sum S1\cup S2\cdots\cup Sn}$ (3)



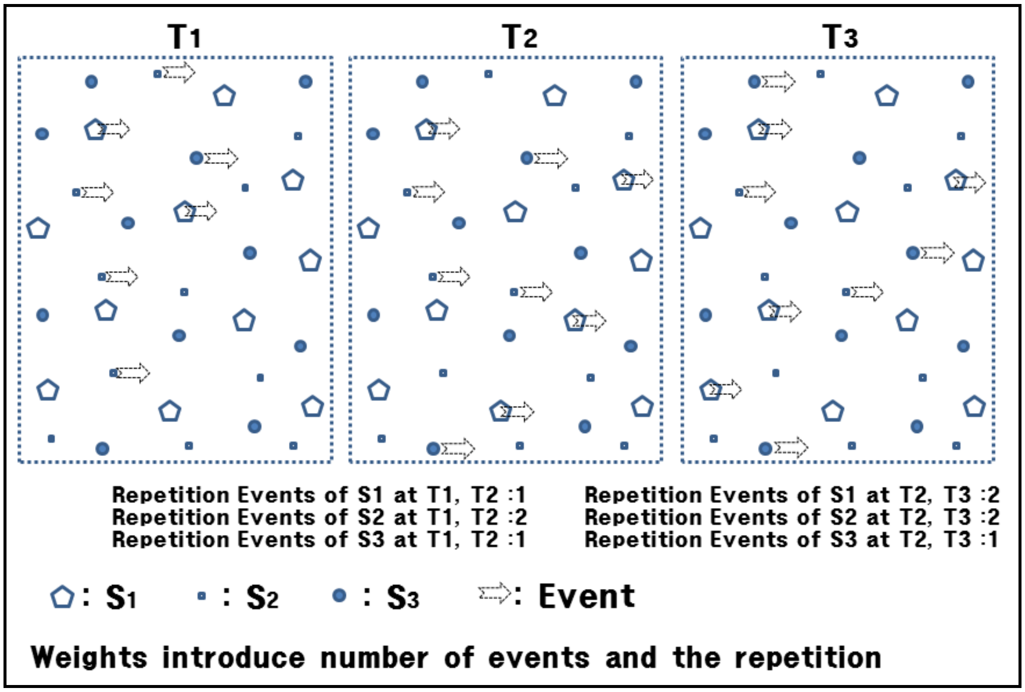


Figure 4. Ways of Weight in the Wireless Sensor Networks; Frequency of Events and the Repetition of Events of Sensors with the Time Lapse

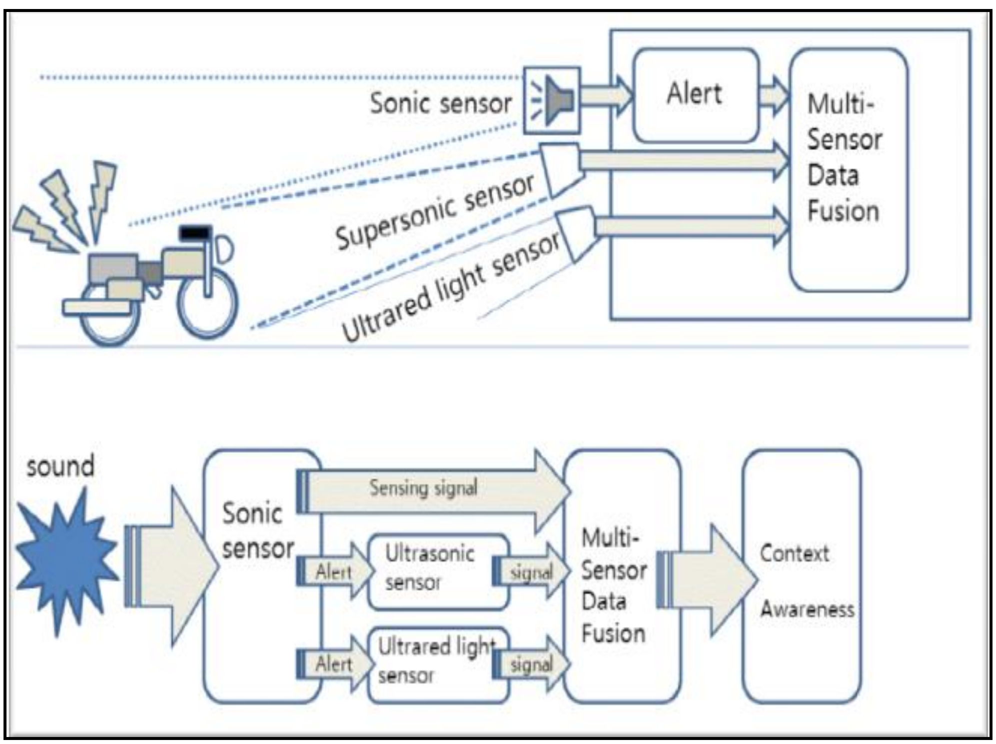


Figure 5. Modeling of Multi-sensor Data Fusion and Context Awareness

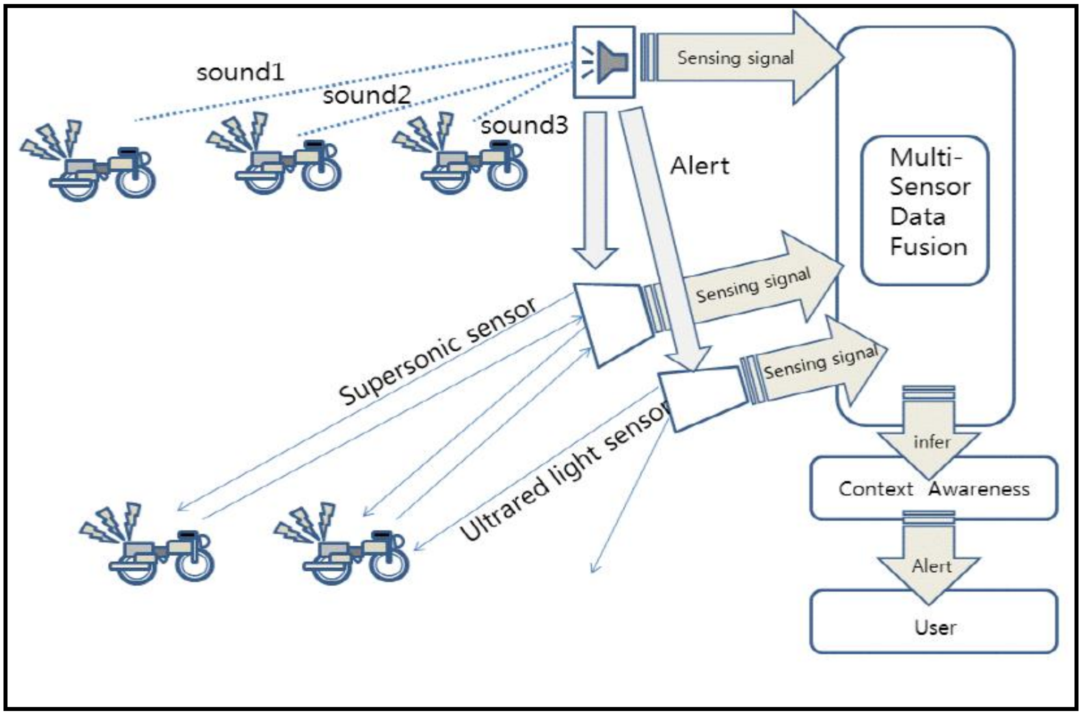


Figure 6. Application of Context Inference Model

4. Experiment and Evaluation

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

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

Focal element	h_1	h_2	h_3	$h_1 \cup h_2$	$h_1 \cup h_3$	$h_2 \cup h_3$	Ω	
	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	$h_1 \cup h_2$	$h_1 \cup h_3$	$h_2 \cup h_3$	Ω	
	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	$pl(B_t)$

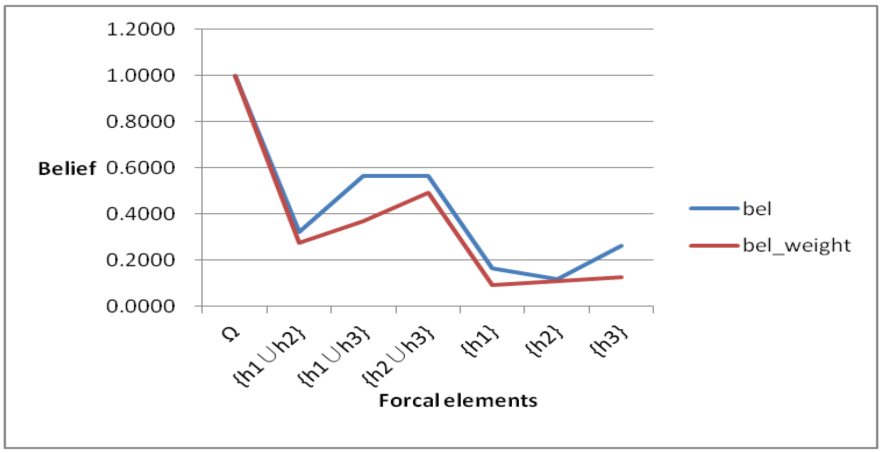


Figure 7. The *belief* is Changed after Weight the BPA, that is make in each Time Zone

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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