Determination of Basic Probability Assignment Based on Assessment of Sensor Measurement

Donghyok Suh*, Jeonghwa Song

*Department of multimedia communication, Far EastUniversity,
Eumseong, Chungbuk, 369-700, Korea
Department of Architecture, Namseoul University,
Cheonan, Chungnam, 331-707, Korea

*hanhwaco@naver.com, songjh@nsu.ac.kr

Abstract

In a wireless sensor network, measures to rationally evaluate the signal detected and reported by the sensor are needed. To infer the context based on the detected signal, determination of basic probability assignment for multi-sensor data fusion using Dempster-Shafer Theory is proposed.

If there is insufficient advance information in a wireless sensor network using different type of sensors, it is helpful to use the difference of the sensed signal values. First is to compare the measurement with the previous measurements and second is to compare the measurement with the filtering reference which is the basis of sensor report. In evaluation through comparison, one can compare the averages in a selected time band, but it may be more rational to compare the variance in evaluation of measured values. We applied such evaluation to determination of basic probability assignment to utilize it for context inference using DST.

Keywords*: Context inference, Wireless sensor network, Basic probability assignment*

1. Introduction

Studies on the context-awareness using wireless sensor networks and the applications providing services are in progress widely. Wireless sensor networks aim to recognize context, efficiently processing the information sent by sensors and provide the personalized service. It is desirable to construct wireless sensor networks with various types of sensors for the context awareness. In wireless sensor network, Dempster-Shafer Evidence Theory (DST) plays an important role in multi-sensor data fusion. DST was, in fact, designed to stochastically represent the uncertainty in a real world. Being able to fuse heterogeneous signal or data, DST was widely used in the fields of image processing and biometrics. DST is used widely to fuse sensor data from the sensor networks consisting of heterogeneous sensors nowadays. In an information security field, the accuracy of network intrusion detection was improved, fusing more than 2 complex factors rather than being based on a single factor. 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. DST was used to infer the cause of context in emergency situations.

The method for DST-based multi-sensor data fusion for context inference is 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.*

Ontology has been widely used in existing studies of context awareness using wireless sensor network. It is well known method of acquiring the context data and modeling it in advance and then matching the signals from the multi-sensors to the model. The weakness of this method is that the system would not be able to recognize anything beyond what it modeled in advance. Next figure shows the context awareness using the information in advance.

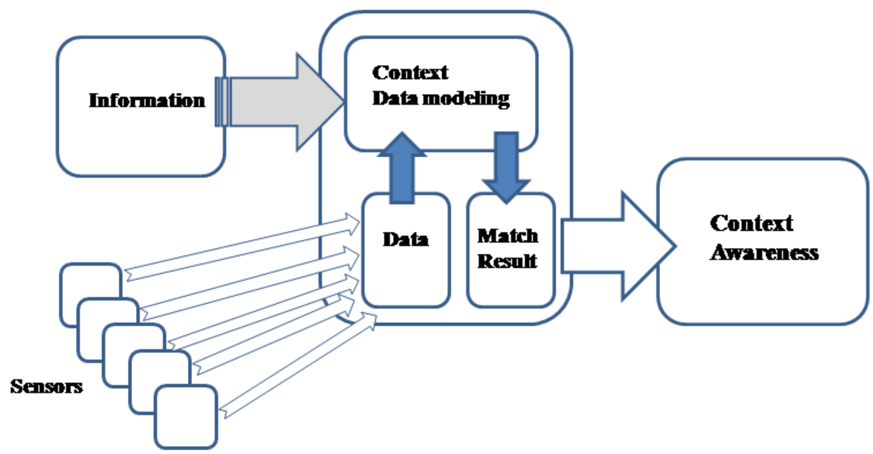

Figure 1. Context awareness using advanced information

Context awareness should have sufficient data and advance information. If not, the sensed values must be rationally evaluated and that must contribute context awareness. Context awareness using the wireless sensor network requires sufficient advance information of the signals sensed and reported by the sensors. If not, the signal values must be correctly evaluated determine whether they will be rationally reflected in context awareness. How should the sensed signals be evaluated to be used as the data for context awareness? One can obtain the advance information of the sensed signals to evaluate the sensed and reported signals. However, since the situations in the real world vary so widely, there may be the cases in which there is no or insufficient advance information. In that case, there must be the measures to evaluate the sensed signals in addition to the attained advance information. As such, there is the need to study the context awareness in the environment where there is insufficient advance information in order to overcome the limitation of context awareness using the wireless sensor network.

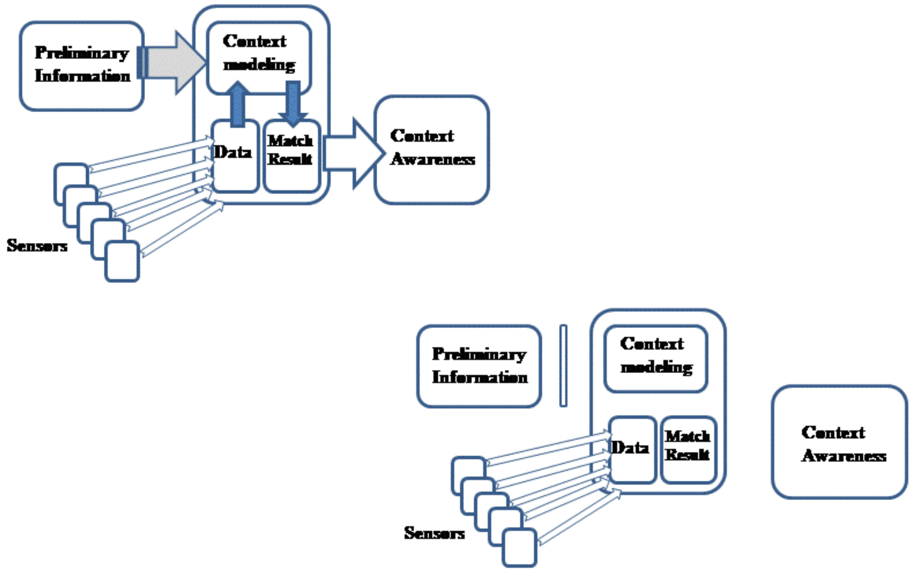

Figure 2. Context awareness without the preliminary information

This paper proposes a novel way to evaluate the data and use it to determine the basic probability assignment function for context inference in the environment where there is insufficient information related to the situation. When evaluating the signals sensed by the sensor in a wireless sensor network, one generally checks whether the sensor measured values have the gap in a time band. Checking whether the sensor measured values show the gap from the specific reference is the basis of evaluating the sensed values. A reference is needed to evaluate the gap of the sensed values. The reference may be the measured valued in the previous time band or the filtering reference which is used whether the sensed signal will be reported. The measured values sensed and reported by the sensors can be evaluated using such reference, but the values reported by many sensors in the ideal wireless sensor network may have various deviations because of sensor error, sensing environment, network problem, etc.

Therefore, it is needed to sort and arbitrate such deviations of the sensed signals showing the different values on the same measurement target. For that, one may consider the average of the measured values. However, the average value has the problem. It is because the extreme errors can be included in the average value. Therefore, other evaluation methods need to be considered. This paper proposes calculation of the variance of the values reported by many sensor motes and use it for evaluation. By evaluating the reported sensed values and determining the basic probability assignment function, feasible context inference will be enabled even when there is insufficient advance information.

This paper is organized as follows: Chapter 2 describes the related studies and Chapter 3 proposes the measures of signal evaluation and BPA determination. Chapter 4 describes the test and evaluation and Chapter 5 presents the conclusion.

2. Related Works

There have been various studies of using DST for data fusion and determining BPA for that. DST is widely used for multi-sensor data fusion [1]. To use DST, there must be the feasible measures to determine BPA. Since the fuzzy theory also requires BPA, studies of how to calculate and determine BPA have received a lot of attention.

T. Ali and P. Dutta proposed methods to determine BPA when minimum, maximum and most likely values of the parameter are known. They developed an extended version of uncertainty measurement in evidence theory in order to calculated total uncertainty of the body of evidence [2]. A.O. Boudraa, A. Bentabet, F. Salzenstein and L. Guillon proposed an image segmentation method based on DST. BPA is estimated in unsupervised way using pixels fuzzy membership degrees derived from image histogram [3]. W. Jiang, A. Zhang, Q. Yang proposed a fuzzy method to obtain basic probability assignment [4]. Wen Jiang proposed a new method to determine BPA based on the distance measure between the sample data under test and the model of attributes of species [5].

However, such methods focus on BPA determination only for data fusion. Since we intend to use DST for data fusion for context awareness, we need to study BPA determination with consideration to context awareness. BPA determination for context awareness must consider the situation. The elements of the situation must be considered and the relation between the sensor measurements and situation must be included and clarified.

3. Evaluation to Determine BPA

Recognizing the situation based on the data detected by various sensors is the important study objective. It is not simple to be aware of the context concerning the sensing target or detection range based on the sensed signals sent by the sensors [6, 7]. Most of the preceding studies of context awareness have focused on obtaining the situation information and modeling it in advance. The situation was evaluated and recognized by first determining and categorizing the scope of the situation to be recognized, defining and modeling the various situations and then mapping the data acquired and reported by the sensors to the data models [8, 9, 10, 11, 12].

However, there will be the situation that exceeds the predefined scope even when the scope is very limited. In that case, the situation must be estimated using only the signals acquired by the sensor. In any case, fusion of the various signals reported by the sensors with the predefined data model is still needed to increase the performance of context awareness.
Therefore, measures of signal processing are very important in context awareness using the wireless sensor network.

Then what is the method of using the signals detected and reported by the sensor as the information needed for context awareness without the reference data? We intend to use data fusion to infer the context and use DST for it by including the evaluation of the significance of the sensed signals during BPA determination which is the key to DST.

The clue of evaluating the signals detected and reported by the sensors is to evaluate the gap of the values sent by the sensor related to the context. For example, the sensor related to fire is the temperature sensor and humidity sensor. Safety of the bridge is related to the sensors detecting the vibration and fracture. Variation of the values detected by such sensors is related to the context. Therefore, evaluation of the difference of the values detected by the sensors will help context awareness. However, in the case of recognizing the situation generated in a large area, the change of the values sent by many sensors must be evaluated. In that case, various problems of the wireless sensor network can be included in the sensor detected signals. Therefore, the change rate of specific measurement and the average of the values measured and reported by various sensors can be useful to evaluate how different the signals reported by the sensors are from the reference and what is the significance of the difference. However, as the values sent by the sensors of the wireless sensor network are sent as the discrete signals not continuous signals and the number of sensors detecting and reporting the signals at each time band can vary, there can be many distortions and errors in the signals. That creates the risk of the average value insensitively recognizing the fine difference.

In this paper, we assume that multiple sensors sense a target or one or more sensors sense a target multiple times during a specific time band. Under such condition, the variance of the sensed values measured in the specific interval in a time band is used as the evaluation criterion in addition to the average.

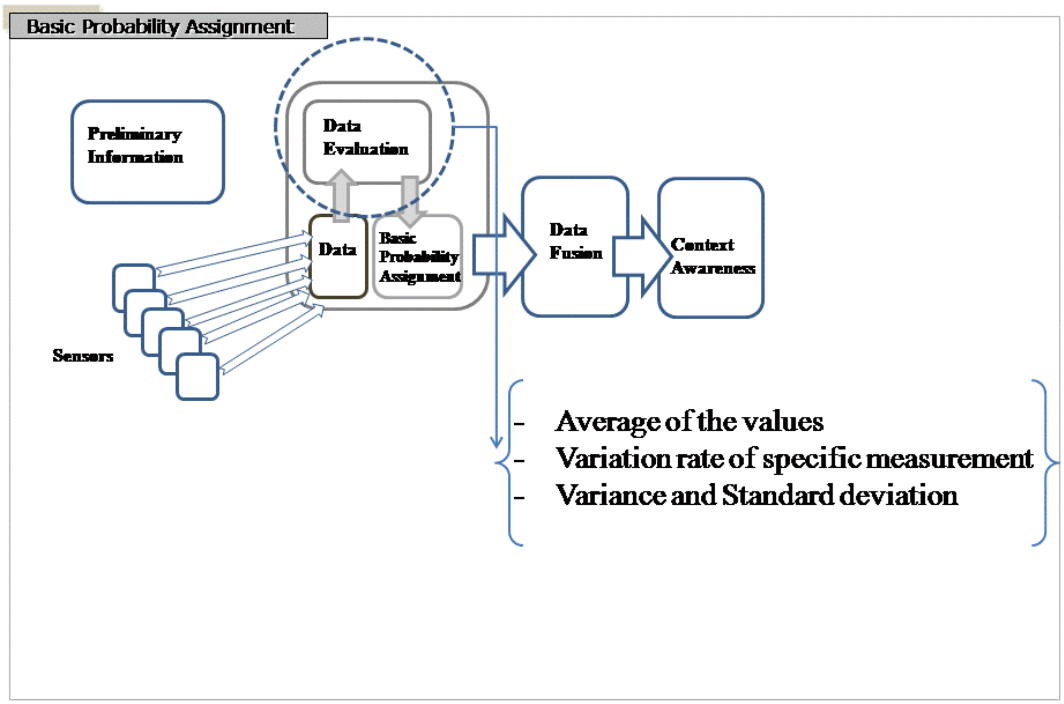

Fig. 3. Evaluate the data for Determination of Basic Probability Assignment

Calculating the average and then the variance of the values sensed by the temperature sensor is described below.

First, we represent the set of values generated by temperature sensors. Then t_n is a sequential array of elements of T, a set of discrete time.

Assuming $I(t_n)$ to be a function with t_n as the definition domain and I as the range, the average $\bar{I}$ can be expressed as follows:

$$\bar{I} = \overline{I(t_n)} = \frac{1}{n+1}\sum_{t=0}^{n} I(t_n)$$

The variance between the function $I(t_n)$ and average $\bar{I}$ of the values input by the temperature sensor at each hour can be expressed as follows:

$$\sigma^2 = \frac{1}{n}\{(\sum_{k=0}^{n} f(t_k^2)) - n(\bar{I})^2\}$$

It is difficult for the variance of signals sent by the inaccurate multiple sensors to maintain the specific value. However, if the continuous variance values maintain a specific value continuously, it is clear that an event was generated. Therefore, we will define a factor expressing how the variance value of past time matches that of current time.

α is defined as the temperature factor.

$$\alpha = \frac{\sqrt{\sigma_{n-1}^2}}{\sqrt{\sigma_n^2}} = \sqrt{\frac{\sigma_{n-1}^2}{\sigma_n^2}} = \frac{\sigma_{n-1}}{\sigma_n}$$

In other words, it is defined as the ratio of standard deviations.

Since the probability of the event generation increases as the value of the temperature factor α approaches 1, the equation can be normalized as follows:

$$I_f^n = \frac{\sqrt{\frac{1}{(1-\alpha_n)^2}}}{\sum_{k=2}^{n}\sqrt{\frac{1}{(1-\alpha_k)^2}}}$$

$1-\alpha_n$ indicates the difference from 1. Root of the square is to ensure that no negative value is generated.

The reason for the reciprocal of $(1-\alpha_n)^2$ to $\frac{1}{(1-\alpha_n)^2}$ is to express that the probability of the event generation increases as the difference from 1 decrease.

Using the method, the average and variance of the sensed values detected and reported by other sensors can also be calculated. We adjust the signal values reported by the sensors to satisfy four properties of BPA and reflect it to BPA determination.

4. Experiment and analysis

We will verify whether the proposed method can be applied to context awareness using the actual wireless sensor network.

The testing environment is described as follows: The temperature sensors, illumination sensors, and sound sensors are operated in pairs and report the sensed values to the sink node every 10 seconds. The sensed values restored in the host through the sink node become the targets of data fusion for context inference every two minutes. BPA must first be determined for data fusion using DST. The variance values of 24 data reported every two minutes are normalized and reflected in BPA calculation. Following table shows the derived variance.

Table 1. Derived variance

Sensor	t_0~t_1	t_1~t_2	t_2~t_3
Temperature	0.091	0.015	0.894
Light	0.018	0.011	0.971
Humidity	0.017	0.081	0.902

Following table shows the BPA for each focal element obtained by normalizing above result values to BPA property and then reflecting them for BPA determination. BPA, which is assigned to the elements structured of sensing data, must reflect the assessed level of contribution to the context by the signals collected and reported by the sensors.

Table 2. Basic Probability Assignment of each focal element at the time slot

Focal elements	$m(t_{0\sim1})$	$m(t_{1\sim2})$	$m(t_{2\sim3})$
Ω	0.135	0.828	0.143
$h_1 \cup h_2$	0.174	0.010	0.144
$h_1 \cup h_3$	0.174	0.038	0.139
$h_2 \cup h_3$	0.113	0.037	0.145
h_1	0.292	0.012	0.138
h_2	0.057	0.009	0.150
h_3	0.056	0.065	0.140

Determination of BPA is the most important step of multiple sensors data fusion based on DST. We can get the *belief* and *plausibility* with BPA.

Table 3. *belief* and *plausibility*

2^{Ω}	t1~t2		t2~t3	
	bel	pl	bel	pl
Ω	1.000	1.000	1.000	1.000
$h_1 \cup h_2$	0.446	0.588	0.423	0.680
$h_1 \cup h_3$	0.721	0.804	0.458	0.711
$h_2 \cup h_3$	0.523	0.722	0.472	0.858
h_1	0.278	0.477	0.142	0.528
h_2	0.111	0.279	0.151	0.542
h_3	0.327	0.554	0.183	0.577

The *belief* and *uncertainty* of each significant element can be calculated after BPA is obtained, and the context inference can be decided based on the *belief* and *uncertainty* of each focal element.

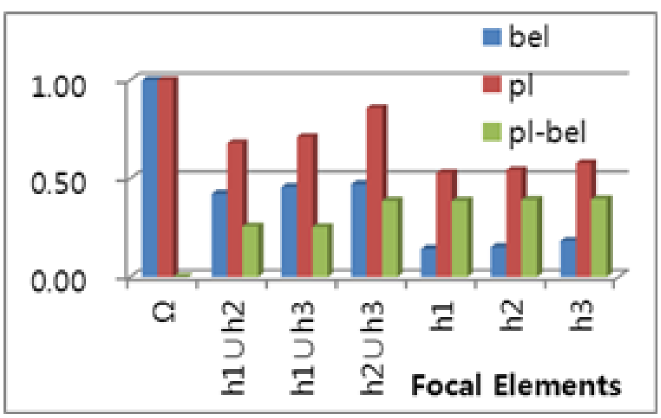

Figure 4. Each focal element's *belief* and *uncertainty*

The test described above shows how the context inference can be achieved based on the evaluation of the sensed values reported by the sensors. There was no advance information of the context. Determining BPA using the evaluation result of the acquired signals enabled multi-sensor data fusion using DST and proved that the inference of the context reported by the sensors could be obtained.

5. Conclusion and Further Study

In an attempt to obtain context awareness through the wireless sensor network, there may be the case of having no advance context information or requiring the additional signal analysis to obtain better context awareness. This paper proposes a novel method of evaluating the values reported by the sensors and using it for calculation BPA in the environment where there is no context information obtained in advance. The differences of measured values in each time band were evaluated and reflected in context inference. The variance of the values reported by the sensors was used as the reference for evaluation. As the result, the significance of the values reported by the sensors could be understood and precisely evaluated despite the limitation of the wireless sensor network which generates numerous errors and problems. For the future studies, using the signal analysis result along with the existing advance context data model to improve the context awareness performance is needed.

Acknowledgements

Funding for this paper was provided by Namseoul university.

References

[1] P. Liuand and J. Zhang, "A Context-Aware Application Infrastructure with Reasoning Mechanism Based on Dempster-Shafer Evidence Theory", VTC Spring IEEE, **(2008)**, pp. 2834–2838.

[2] T. Ali and P. Dutta, "Methods to Obtain Basic Probability Assignment in Evidence Theory", International Journal of Computer Applications, vol. 38, no. 4, **(2012)**.

[3] A. O. Boudraa, A. Bentabet, F. Salzenstein and L. Guillon, "Dempster-Shafer's Basic Probability Assignment Based on Fuzzy Membership Functions", Electronic Letters on Computer Vision and Image Analysis, vol. 4, no. 1, **(2004)**.

[4] W. Jiang, A. Zhang and Q. Yang, "Fuzzy Approach to Construct Basic Probability Assignment and Its Application in Multi-Sensor Data Fusion Systems", Chinese journal of sensors and actuators, vol. 21, no. 10, **(2008)**, pp. 1717-1720.

[5] W. Jiang, "A New Method to Determine BPA in Evidence Theory", Journal of Computers, vol. 6, no. 6, **(2011)**.

[6] U. Rakowsky, "Fundamentals of Dempster-Shafer theory and its applications to system safety and reliability modeling", International journal of reliability, quality, and safety engineering, vol. 14, no. 6, **(2007)**, pp. 579-602.

[7] Y. O. Han and D. H. Suh, "Multi-sensor Data Fusion with Dynamic Component for Context Awareness", International Journal of Smart Home, vol. 6, no. 6, **(2012)**, pp. 107-116.

[8] D. H. Suh and C. K. Ryu, "A Novel Weighting Method for Context Inference", International Journal of Multimedia and Ubiquitous Engineering, vol. 8, no. 1, **(2013)**, pp. 91-100.

[9] Q. Liu, N. Linge and F. Gao, "A Context-aware Protocol for Location Discovery Exchange in a Ubiquitous Environment", International Journal of Multimedia and Ubiquitous Engineering, vol. 7, no. 2, **(2012)**, pp. 177-182.

[10] M. Wenying and D. Zuchun, "A Novel Template Weighted Match Degree Algorithm for Optical Character Recognition", International Journal of Smart Home, vol. 7, no. 3, **(2013)**, pp. 261-270.

[11] K. S. Kim and Y. S. Choi, "Bayesian Network Approach to Computerized Adaptive Testing", International Journal of Smart Home, vol. 6, no. 3, **(2012)**, pp. 75-82.

[12] Y. C. Ngeow, A. K. Mustapha, E. Goh, H. K. Low and D. Chieng, "Context-aware Workflow Management Engine for Networked Devices", International Journal of Multimedia and Ubiquitous Engineering, vol. 2, no. 4, **(2007)**, pp. 33-48.