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Hierarchical Multi-sensors Data Fusion for Enhanced Context Inference

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Abstract

Dempster-Shafer Evidence Theory can infer the context only with some native sensed signals but its number of assumptions is limited, compared to the number of evidence. In this research, we proposed a method that can increase the number of sensors collecting symptoms for more dynamic contextual inference yet with reduced calculation load increase. This is possible by clustering sensors with relevance to a situation and fusing data hierarchically.

Keywords: *Context inference, Data fusion, Ubiquitous sensor networks*

1. Introduction

Dempster–Shafer theory (DST) was introduced as a probability theory describing the uncertainty of the real world. While Baeysian theory denies any uncertain event, DST made possible to express uncertainties, that is, the status of not true or false but uncertain. Such expansion of expression enabled new engineering application beyond the original goals of the mathematical theory. In each area of the modern science, the necessity for multi-sensor data fusion has increased. This multi-sensor data fusion has given important clues to move forward diverse areas such as geographic information, robot science, information security, medical diagnosis, and biometrics. As ubiquitous and relevant areas have been actively researched, DST has expanded its application.

Especially, DST has been utilized in sensor network area to adopt heterogeneous sensors to obtain advanced state contextual information. Multi-sensor data fusion was first designed for a military purpose in the 1960s to estimate the trajectory of a projectile. Other than Kalman equation and DST, artificial neural network and fuzzy theory have been utilized as a good fusion method. Compared to other methods, DST is better in estimating contextual situation only with several simple measurement values. Kalman equation tends to be used more for location tracking and is limited in its capacity to recognize the diversity of contextual situation. The neural network processes data based on accumulated learning experience so it consumes longer time before producing a result. Swift context inference and fast response to rapid changes can hardly be the area of the theory. DST or Fuzzy theory-using data fusion does not have such a problem but it uses BPA as the base of processing. Here, the problem is the number of focal element in the DST. Assumptions are established to recognize a certain situation or infer some reasons of a specific event and the diversity of such an assumption is limited under those methods.

In the real world, contexts are largely diverse. It is extremely difficult to recognize such diversity only by using a few signals detected by several sensors from a distance. For any event taking place in the real world, whose information has not been obtained previously, or any event that goes beyond the boundary of data modeling, they used DST by evaluating the signals from sensors or interpreting the implied meaning of those signals and fussing them to

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make inference. In such a manner, the weak point of the existing previously-gathered-data-based scheme could be covered. This is one of the strong points of DST-using data fusion.

There are, also, problems in DST-based data fusion. First is to determine focal element. Here, focal elements are corresponding to an assumption. That is, focal element means the number of cases when n number of evidence appear, or the number of reasons estimated based on the information obtained by n number of sensors. And the number of focal element is 2n. And this is where the problem lies. If we use more diverse kinds of multi sensors, we can get more accurate and higher level of contextual information to estimate a situation. But the calculation increases. Yet, if fewer sensors are used, the numbers of assumptions and cases themselves will grow fewer too. Inferring a situation or its reasons behind, in such an environment, could face a very strict limitation sometimes. Therefore, we need a method of using many sensors while keeping the calculation load lower. If this becomes possible, we will have a higher possibility of obtaining more accurate contextual information with many diverse sensors.

This study suggests a method to reduce the calculation load while involving diverse kinds of sensors for DST-using multi-sensor data fusion. Through the method suggested herein, we seek to demonstrate how to obtain higher-level contextual information only within controlled increase in calculation.

The study includes reviewing basic theories and related research in Chapter 2, explaining the core of the theory from the study in Chapter 3, conducting an experiment with the method and showing the result in Chapter 4, and describing the conclusion in Chapter 5.

2. Related Research

Multi-sensor data fusion has been studied in various areas, including image processing, information security, robot remote control, and system error calibration [1]. R. Sharma, *et al.*, proposed a novel method for intrusion awareness using data fusion and SVM classification. Data fusion work on the biases of features gathering of event. Support vector machine is super classifier of data. They used SVM for the detection of closed item of ruled based technique [2].

X. Mao, *et al.*, established a feedback-involved Federated Kalman Filter, consisting of two subsystem filters (Gyros/GPS and Gyros/Star-sensor) to obtain global attitude estimation after an information fusion process. Taking the sensors' different update rates into account, these two subsystem filters are conducted under a variable step size state prediction method. To improve the fault tolerant capacity of the attitude determination system, they designed malfunction warning factors, based on the principle of residual verification [3].

Y. Sun, *et al.*, proposed a novel multi-sensor data fusion method based on twice spatial-temporal correlation. Considering the correlation of the space and the time, the method constructs a spatial-temporal correlation matrix. Then a measure equation combining the consistency and the stability of multi-sensor is built. Applying the equation, they get the real-time weight of each sensor, which is used for the data fusion of the measurement system [4].

A. R. Rababaah proposed a new data fusion model that contributes to the area of multi-senor/source data fusion. The new fusion model relies on image processing theory to map stimuli from sensors onto an energy map and uses non-linear convolution to combine the energy responses on the map onto a single fused response map. This response map is then fed into a process of transformations to extract an inference that estimates the output state response as a normalized amplitude level. This new data fusion model is helpful to identify sever events in the monitored environment [5].

M. G, Song, *et al.*, used multi-sensor data fusion technique to process a variety of sensing information sent by a robot, in order to correct the robot's posture and control its vibration [6]. J. Y. Lee, *et al.*, assigned multiple sensors to an unmanned aircraft in order to estimate the state of the unmanned aircraft and fused the sensing data sent by the sensors to estimate the state of the air craft [7]. Huadong Wu studied a data fusion model to acquire the improved situational information in the wireless sensor network, and used Dempster-Shafer Theory for data fusion [8].

In the DST-using multi-sensor data fusion research, the number of focal element – the number of assumptions engaged in estimating a situation, is determined by the number of evidence. If the number of evidence appeared is Θ, the number of focal element is 2Θ.

In the multi-sensor data fusion for situational context estimation, the number of focal element is rather limited and this can work as an obstacle in inferring the real world situation. Making an inference only within the limited number of focal element is bound to be restricted, given the enormous diversity of the real worlds. We can increase the number of evidence or sensors that collect evidence. But doing so causes another problem: The rapid increase of calculation amount.

In this paper, for effective obtaining of higher level contextual estimation, a method is suggested to increase the kinds of sensors of the sensor network but, at the same time, to reduce the calculation amount.

3. Data Fusion with Reduced Calculation for Contextual Inference

Ontology is preferred in contextual inference based on a sensor network. However, as actual situations are diverse and dynamic, any method relying on previously accumulated information such as the ontology method can always be vulnerable. Of course, inferring only by using sensed signals is also vulnerable. More kinds of sensors in sensing signal-based data fusion would be favorable for higher accuracy but the calculation amount will also increase too. This study, in this sense, proposes a method to increase the sensor kind but cluster them according to an appropriate criterion and perform data fusion in each cluster so that the results are converged again.

In the DST-using data fusion, if the kinds of sensors are n, its accompanied number of assumptions will be 2n. The more the sensor kinds grow, the larger the number of assumptions will be and its following calculation load will also surge. The overall calculation load, however, can be reduced still with larger number of sensors involved, if those sensors are clustered and fused primarily in the lower cluster.

Then, next consideration is which criteria should be followed in clustering various sensors.

At first, the characteristics of the sensing composition and sensing goal should be included in data processing. If the factors consisting of a situation have relations with the factors affecting the situation, the relations should be included in something to be considered for context awareness.

What is needed in the environment is to process together the sensors which show similar composition. In other words, it is necessary to identify the goal of each sensor group and perform fusion processing of the groups. The sensor data processing structure is called the hierarchical calculation structure in fusion processing. The fusion processing of the data measured by sensors of a sensor group is performed as follows:

The reasons that fusion processing should be performed from a sensor group are as follows. First, those sensors in a sensor group do not have the same type, Second, that it is aimed at fusing the data measured and reported by different sensors and producing a higher level of result, and Third, that each sensor does not always have the same weight of monitoring. Sometimes, the data detected by sensors work together with other sensors' and have similar weight, and sometimes, they don't. That is because multi-sensor data fusion suggests a rational method.

Figure 1. (a) Data fusion totally (b) Hierarchical data fusion

The sequence process of data fusion in lower cluster and upper cluster is presented as shown in the following figure.

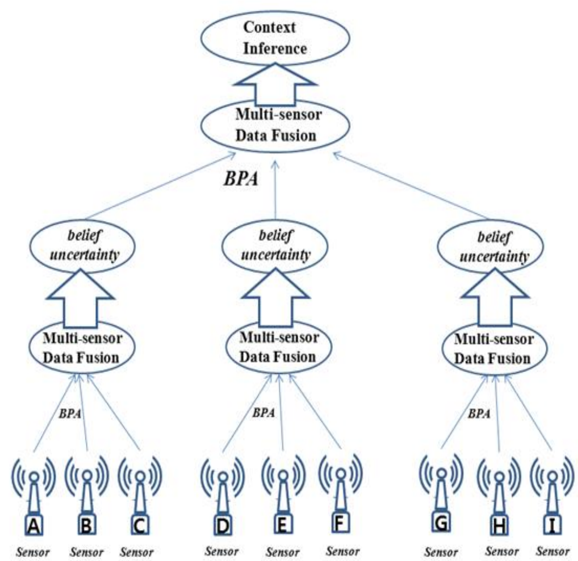

Figure 2. Data fusion procedure

In the structure, the calculation procedure of data fusion is a bottom-up one. Data fusion consists of step 1 and step 2. The step 1 data fusion is performed in lower sensor cluster. Based on the first fusion processing result, the step 2 data fusion is performed. Step 1 is the lower layer, and step 2 is the upper layer. The processing procedure is presented with a formula as follows:

ⓕ: data fusion,

$$m_1 \oplus m_2 \oplus m_3(A) = \begin{cases} 0 & ,\text{if } A \neq \phi \\ \dfrac{\sum_{A_i \cap B_j \cap C_k = A} m_1(A_i) \cdot m_2(B_j) \cdot m_3(C_k)}{\sum_{A_i \cap B_j \cap C_k \neq A} m_1(A_i) \cdot m_2(B_j) \cdot m_3(C_k)} & \end{cases}$$

$M_1 = m_1 \oplus m_2 \oplus m_3(A)$, $M_2 = m_1 \oplus m_2 \oplus m_3(B)$, and $M_3 = m_1 \oplus m_2 \oplus m_3(C)$

$$M_1 \oplus M_2 \oplus M_3(A) = \begin{cases} 0 & ,\text{if } A \neq \phi \\ \dfrac{\sum_{A_i \cap B_j \cap C_k = A} M_1(A_i) \cdot M_2(B_j) \cdot M_3(C_k)}{\sum_{A_i \cap B_j \cap C_k \neq A} M_1(A_i) \cdot M_2(B_j) \cdot M_3(C_k)} & \end{cases}$$

Here is one thing to be concerned. That is how far the first fusion should be performed. For the issue, it is possible to think about two methods.

The first one is that *belief* and *plausibility* of each focal element are calculated in the first fusion. In other words, in the first fusion, BPA of each focal element in cluster is determined, and on the basis of the determination, it is normalized to the BPA for the second fusion.

The second one is that, in the first fusion, BPA, belief and uncertainty of each focal element are calculated. The choice of the two methods is directly dependent on the way of calculating BPA. In other words, it is to investigate which one is valid among the method of calculating BPA in the first fusion and making normalization, and then of directly using the normalization in the second fusion, and the method of calculating belief, plausibility and uncertainty on the basis of BPA acquired in the first fusion, and then of determining the BPA necessary for the second fusion.

In the case of the first method, it is hard to emphasize clear differentiation in comparison of uniform data fusion rather than hierarchical data fusion. That is because BPA of each focal element of sensors that constitute the sensor cluster of the lower layer goes up to the upper layer. And, based on that, BPA is determined for the second fusion.

Now, the method of determining BPA, which is essential for hierarchical multi-sensor data fusion using DST, is discussed. Since determining BPA is a key to multi-sensor data fusion using DST, this work proposes the method of determining the BPA necessary for hierarchical data fusion.

4. An Experiment and Evaluation

The method presented in this paper was tested as follows:

In the experiment for this study, the data from the 6 sensors above were fused in two methods. And the results were compared. Our first experiment is to fuse the whole 6 sensors overall. The data from the ultrasonic sensor is e_1; from infrared ray sensor, e_2; from acceleration sensor, e_3; from humidity sensor, e_4; from temperature sensor, e_5; from CO_2 sensor, e_6.

Here, *n*={focal elements} is $2^6 = 64$.

Table 1 shows the 64 different assumptions inferred from the $e_1 \sim e_6$ data along with the BPA for each assumption. By utilizing these BPA, we calculated *belief* and *uncertainty* according to DST and the results are shown in Table 1.

Table 1.Total fusion of $e_1 \sim e_6$

2^{Ω}	$m(A_k)$	$bel(A_k)$	$pl(A_k)$	pl-bel
h_1	0.0017	0.0017	0.5563	0.5546
h_2	0.0046	0.0046	0.5733	0.5688
h_3	0.0000	0.0000	0.5000	0.5000
h_4	0.0021	0.0021	0.5333	0.5313
h_5	0.0125	0.0125	0.7000	0.6875
h_6	0.0104	0.0104	0.6667	0.6563
$h_1 \cup h_2$	0.0063	0.0125	0.8000	0.7875
$h_1 \cup h_3$	0.001667	0.0033	0.7633	0.7600
$h_1 \cup h_4$	0.00375	0.0075	0.7800	0.7725
$h_1 \cup h_5$	0.014167	0.0283	0.8633	0.8350
$h_1 \cup h_6$	0.012083	0.0242	0.8467	0.8225
$h_2 \cup h_3$	0.004583	0.0092	0.7867	0.7775
$h_2 \cup h_4$	0.006667	0.0133	0.82 63	0.8129
$h_2 \cup h_5$	0.017083	0.0342	0.8867	0.8525
$h_2 \cup h_6$	0.015	0.0300	0.8700	0.8400
$h_3 \cup h_4$	0.002083	0.0042	0.7667	0.7625
$h_3 \cup h_5$	0.0125	0.0250	0.8667	0.8417
$h_3 \cup h_6$	0.010417	0.0208	0.8333	0.8125
$h_4 \cup h_5$	0.014583	0.0292	0.8667	0.8375
$h_4 \cup h_6$	0.0125	0.0250	0.8500	0.8250
$h_5 \cup h_6$	0.022917	0.0458	0.9333	0.8875
$h_1 \cup h_2 \cup h_3$	0.00625	0.0250	0.9000	0.8750
$h_1 \cup h_2 \cup h_4$	0.008333	0.0333	0.9083	0.8750
$h_1 \cup h_2 \cup h_5$	0.01875	0.0750	0.9500	0.8750
$h_1 \cup h_2 \cup h_6$	0.016667	0.0667	0.9417	0.8750
$h_1 \cup h_3 \cup h_4$	0.00375	0.0150	0.8900	0.8750
$h_1 \cup h_3 \cup h_5$	0.014167	0.0567	0.9317	0.8750
$h_1 \cup h_3 \cup h_6$	0.012083	0.0483	0.9233	0.8750
$h_1 \cup h_4 \cup h_5$	0.01625	0.0650	0.9400	0.8750
$h_1 \cup h_4 \cup h_6$	0.014167	0.0567	0.9317	0.8750
$h_1 \cup h_5 \cup h_6$	0.024583	0.0983	0.9733	0.8750
$h_2 \cup h_3 \cup h_4$	0.006667	0.0267	0.9017	0.8750
$h_2 \cup h_3 \cup h_5$	0.017083	0.0683	0.9433	0.8750
$h_2 \cup h_3 \cup h_6$	0.015	0.0621	0.9350	0.8729
$h_2 \cup h_4 \cup h_5$	0.019167	0.0767	0.9517	0.8750
$h_2 \cup h_4 \cup h_6$	0.017083	0.0683	0.9433	0.8750
$h_2 \cup h_5 \cup h_6$	0.0275	0.1100	0.9850	0.8750
$h_3 \cup h_4 \cup h_5$	0.014583	0.0583	0.9483	0.8900
$h_3 \cup h_4 \cup h_6$	0.0125	0.0500	0.9250	0.8750
$h_3 \cup h_5 \cup h_6$	0.022917	0.0917	0.9667	0.8750
$h_4 \cup h_5 \cup h_6$	0.025	0.1000	0.9750	0.8750
$h_1 \cup h_2 \cup h_3 \cup h_4$	0.008333	0.0667	0.9542	0.8875
$h_1 \cup h_2 \cup h_3 \cup h_5$	0.01875	0.1500	0.9750	0.8250
$h_1 \cup h_2 \cup h_3 \cup h_6$	0.016667	0.1354	0.9708	0.8354
$h_1 \cup h_2 \cup h_4 \cup h_5$	0.020833	0.1667	0.9792	0.8125
$h_1 \cup h_2 \cup h_4 \cup h_6$	0.01875	0.1500	0.9750	0.8250
$h_1 \cup h_2 \cup h_5 \cup h_6$	0.029167	0.2333	0.9958	0.7625
$h_1 \cup h_3 \cup h_4 \cup h_5$	0.01625	0.1300	0.9700	0.8400
$h_1 \cup h_3 \cup h_4 \cup h_6$	0.014167	0.1133	0.9658	0.8525
$h_1 \cup h_3 \cup h_5 \cup h_6$	0.024583	0.1967	0.9867	0.7900
$h_1 \cup h_4 \cup h_5 \cup h_6$	0.026667	0.2133	0.9908	0.7775
$h_2 \cup h_3 \cup h_4 \cup h_5$	0.019167	0.1533	0.9758	0.8225
$h_2 \cup h_3 \cup h_4 \cup h_6$	0.017083	0.1367	0.9717	0.8350
$h_2 \cup h_3 \cup h_5 \cup h_6$	0.0275	0.2200	0.9925	0.7725

$h_2 \cup h_4 \cup h_5 \cup h_6$	0.029583	0.2367	0.9967	0.7600
$h_3 \cup h_4 \cup h_5 \cup h_6$	0.025	0.2000	0.9875	0.7875
$h_1 \cup h_2 \cup h_3 \cup h_4 \cup h_5$	0.020833	0.3333	0.9896	0.6563
$h_1 \cup h_2 \cup h_3 \cup h_4 \cup h_6$	0.01875	0.3000	0.9875	0.6875
$h_1 \cup h_2 \cup h_3 \cup h_5 \cup h_6$	0.029167	0.4246	0.9979	0.5733
$h_1 \cup h_2 \cup h_4 \cup h_5 \cup h_6$	0.03125	0.5000	1.0000	0.5000
$h_1 \cup h_3 \cup h_4 \cup h_5 \cup h_6$	0.026667	0.4267	0.9954	0.5688
$h_2 \cup h_3 \cup h_4 \cup h_5 \cup h_6$	0.029583	0.4733	0.9983	0.5250
$h_1 \cup h_2 \cup h_3 \cup h_4 \cup h_5 \cup h_6$	0.03125	1.0000	1.0000	0.0000

In the second experiment, we grouped sensors e_1~e_3 as a cluster and e_4~e_6 as the other cluster. With the data from e_1~$e_{3,}$ we formed focal element and arranged their BPA and with the data from e_4~e_6 we formed focal element and calculated their BPA. Table 2 and 3 shows the results.

Table 2. Results of fusion with e_1~e_3

2^Ω	$m(A_k)$	$bel(A_k)$	$pl(A_k)$	pl-bel
h_1	0.0667	0.0667	0.6333	0.5667
h_2	0.1833	0.1833	0.8667	0.6833
h_3	0.0000	0.0000	0.5000	0.5000
$h_1 \cup h_2$	0.2500	0.5000	1.0000	0.5000
$h_1 \cup h_3$	0.0667	0.1333	0.8167	0.6833
$h_2 \cup h_3$	0.1833	0.3667	0.9333	0.5667
$h_1 \cup h_2 \cup h_3$	0.2500	1.0000	1.0000	0.0000

Table 3. Results of fusion with e_4~e_6

2^Ω	$m(A_k)$	$bel(A_k)$	$pl(A_k)$	pl-bel
h_4	0.0208	0.0208	0.5417	0.5208
h_5	0.1250	0.1250	0.7500	0.6250
h_6	0.1042	0.1042	0.7083	0.6042
$h_4 \cup h_5$	0.1458	0.2917	0.8958	0.6042
$h_4 \cup h_6$	0.1250	0.2500	0.8750	0.6250
$h_5 \cup h_6$	0.2292	0.4583	0.9792	0.5208
$h_4 \cup h_5 \cup h_6$	0.2500	1.0000	1.0000	0.0000

The third and fifth column is the results of *belief* and *uncertainty* calculation for each BPA. Here, we re-calculate inter-cluster fusion. Table 4 is the outcome of both cluster BPA-based fusion and the processing of *belief* and *uncertainty* of Table 3.

Table 4. Final fusion and the results

2^Ω	$m(A_k)$	$bel(A_k)$	$pl(A_k)$	pl-bel
$h_1 \cup h_2$	0.255319	0.2500	0.7500	0.5000
$h_5 \cup h_6$	0.234043	0.2292	0.7292	0.5000
$h_1 \cup h_2 \cup h_5 \cup h_6$	0.510638	0.9792	0.9792	0.0000

Finally, we compared the calculation load in Table 4. As shown from the table, fusing the two clusters of 3 sensors required lower calculation than fusing the whole 6 sensors at once. And in terms of contextual inference, the former method showed no poorer performance in estimating which factors worked behind an event. The variance of projective values from data group A is decreasing from t_2 as seen in the Table 1. This indicates a particular context occurrence. To infer a cause for a particular context, the Table 4 is used.

5. Conclusion

In the real world, situations are vastly dynamic. In multi-sensor data fusion using DST, focal element represents an event caused by evidence or an assumption presumed based on symptoms. DST can infer a situation only with some native signals but its number of assumptions is limited, compared to the number of evidence. In this research, we proposed a method that can increase the number of sensors collecting symptoms for more dynamic contextual inference yet with reduced calculation load. This is possible by clustering sensors with relevance to a situation and fusing data hierarchically.

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