An Evidential Fusion Network based Context Reasoning for Smart Media Service

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Abstract— **For effective smart media service, a reliable and confidential context recognition is required to prepare and react properly. However, it is difficult to achieve a higher confidence level for several reasons. First, raw data from multiple sensors have different degrees of uncertainty. Second, generated contexts can indicate conflicting results, even though they are acquired by simultaneous operations. In this paper, we demonstrate an Evidential Fusion Network (EFN) based context reasoning for smart media service. For this we conduct the context classification and state-space based context modelling. Then, we perform the static evidential fusion process (SEFP) to obtain a higher confidence level of contextual information. It processes sensor data with an evidential form based on the Dezert-smarandache theory (DSmT). The execution with proposed example scenario demonstrates that the DSmT approach based on PCR5 rule performs better than the DST approach based on Dempster's rule.**

Keywords—**Context reasoning, sensor data fusion, smart media service**

I. Introduction

Recently, from television to camera, traditional media consuming and generating devices are getting smarter by equipped with multi-functions, linked to other devices, and connected to the service systems or content markets. Media consumption environment is also getting smarter by equipped with multi-sensors and connected with service platforms or management systems. In addition, the new devices supporting media consumption and generation have emerged with new abilities. Such change enables and empowers the evolution of media service to provide contents organically and smartly.

For the smart media service upon the multiple smart devices within the smart environment, a confidential context reasoning scheme is required. In order to react in an appropriate way, perceived user activities need to be identified carefully to catch their needs or intends correctly. Data aggregation and fusion from multi-sensor and multi-source can generate more accurate and reliable context in a pervasive information environment. However, as much the confidence level of generated context is important, obtaining one is difficult because; 1) multiple sensors may provide unreliable information due to faults, operational tolerance levels, or corrupted data; 2) chance of inaccurate sensor readings can produce misunderstandings that lead to incorrect services; 3) some sensors provide information only at an abstract level, which can include uncertainty to some extent; and 4) it gets more ambiguous if data from multiple sensors are corrupted or conflicted.

To perform the context reasoning that can produce a higher confidence level of contextual information, we adopt the static evidential fusion process (SEFP) proposed in [1]. Different from the DST approach based on Dempster's rule, the [1] takes DSmT approach based on PCR5 rule. Hence, we execute both approaches with example smart media service scenario. The decision is taken by the maximum of the pignistic probability function and the results shows that the DSmT approach based on PCR5 rule produces less mass of ignorance and higher confidence level than that of the DST approach based on Dempster's rule.

In the rest of this paper, the context classification, modelling, and reasoning method to generate contexts for smart media service is described. We also demonstrate the context reasoning processes based on the proposed example scenario for smart media service. After comparing the results in terms of the mass of ignorance and confidence level, we conclude the paper.

II. Context Classification, Modelling, and Reasoning Method

A. *Context Classification and modelling*

Before we perform the context reasoning, classifying the context of the situations for intended services is required. However, context classification is not easy since there are unlimited numbers of ways to describe an event or an object. Hence, in this paper, we define a relation-dependency based context classification and construct a state-space context modelling based on [9]. The dependency is a special type of relationship that exists not between entities and attributes but between associations themselves [7]. The dependencies between the objects or the sensors are not defined by the nature but by our interest, i.e., what we want to know. As the observation purpose or the goal of the context awareness differs, the dependencies between related objects or sensors gets different. Without the knowledge and understanding on such dependencies, appropriate decisions cannot be made by the context-aware service functions and can cause the wrong operations. Therefore, we consider the relation dependency approach based on spatial–temporal criteria. In this approach, contexts are represented by three relation dependencies: 1) discrete facts; 2) continuous facts; and 3) client's interaction. Then, following the state-space-based context modeling with an evidential form is defined in [9], static weighting factors of the selected data within the given time and location are applied to represent the quality of data. This context modelling consists of a hierarchical interrelationship among multiple sensors, related contexts, and relevant activities within a selected region.

B. SEFP

To obtain a higher confidence level of contextual information, context reasoning is performed by the static evidential fusion process (SEFP) proposed in [1]. The procedures of the SEFP consist of seven steps:

1) Represent the evidence on each sensor as a mass function in the evidential framework.
2) Apply a static discounting factor (error rate) (r) into a sensor to get sensor credibility.
3) Translate a multivalued mapping representing relationships between sensors and associated objects to make a context attribute.
4) Aggregate context attributes and then translate to make a context state.
5) Apply different static weighting factors to each context state to sum up context states.
6) Apply the PCR5 rule to context states to achieve the consensus with the conflict mass and then to redistribute the partial conflicting mass.
7) Calculate the belief levels, uncertainty levels, and the maximum of pignistic probability of each activity and then make a decision.

Using evidential fusion processes such as the frame of discernment, the multivalued mapping, the combination rule, and the belief filter, context reasoning based on evidential fusion networks can be applied. In particular, we process sensor data with an evidential form based on the Dezert–Smarandache Theory (DSmT) [2]–[4]. DSmT reduces the uncertainty level and obtains a rational decision of contextual information using a proportional conflict redistribution 5 (PCR5) combination rule [10] and a generalized pignistic transformation (GPT) [5]. The PCR5 rule redistributes the partial conflicting mass to the elements involved in the partial conflict, considering the canonical form of the partial conflict. The PCR5 rule is the most mathematically exact redistribution of conflicting mass to nonempty sets following the logic of the conjunctive rule [3]. Hence, the PCR5 rule is considered a combination rule in this paper. To take a rational decision, GPT generalizes the classical pignistic transformation (CPT), which has two levels of processes: 1) creedal (for combination of evidence) and 2) pignistic (for decision making) within the DSmT framework [11], [12]. The beliefs are represented by belief functions at the creedal level, and then, the beliefs induce a probability function at the pignistic level to make decisions. The decision is also taken by the maximum of the pignistic probability function.

III. Applied Context Reasoning for Smart Media Service by SEFP

A. Applied scenario

When a client enjoys a media service, various situations can happen. Nevertheless, the most important contextual information is whether the client is interested in current content or not. Since the client's interest can be regarded in many ways, to elaborate the ambiguity, we try to figure out whether the client is concentrated on watching the content or not. For this, we can monitor the client's reactions or actions while consuming the content. The reactions can be detected by multiple sensors. For example, client's face recognition and expression identification can be done by image comparison and analysis using photos taken by a camera deployed or embedded on the smart media device. Sound and motion are also good resources to catch the client's mood and context, captured by an audio sensor and an infrared sensor also embedded or deployed on the device. On the other hand, the client's actions can be detected directly by the input signals from the lights, remote controllers, and second screen devices (e.g., smart phone, touch pad, etc.). Those signals can be interpreted as the sign of distraction; if the client is really concentrated on the scenes playing on the screen, he/she would not take any actions especially changing environment, channel, or working on other devices. The simultaneous actions on second screen devices can be about the content currently watching, but still, while he/she takes the action, they cannot pay full attention to the screen.

Thus, we utilize six types of different sensors in this scenario. Each sensor has a predefined threshold, and their operations can be represented by evidential forms. We can derive a SEN based on these simplified two cases, as shown in Fig. 1. We then find out more closely correct situations through context reasoning by calculating the belief, uncertainty, and maximum pignistic probability levels of each related activity. To calculate them, we assume that a discounting rate [error rate (*r*)] and a static weighting factor of

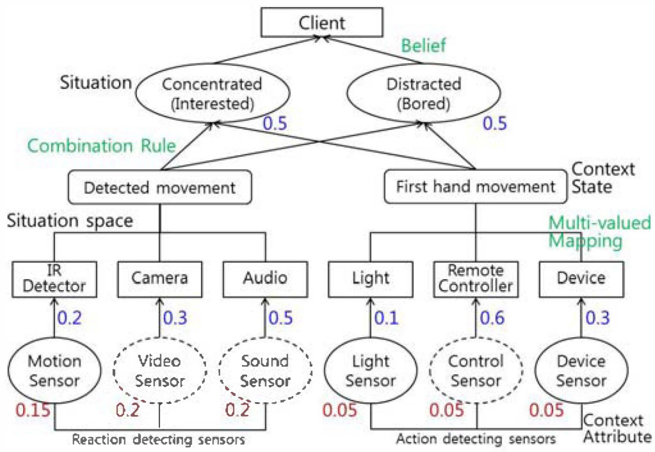

Figure 1. Example of a context reasoning for smart media service based on the SEN

each sensor are fixed. In addition, we assume that a static weighting factor of the motion sensor, the video sensor, the sound sensor, the light sensor, the control sensor, and the device sensor are 0.2, 0.3, 0.5, 0.1, 0.6, and 0.3, respectively. Three sensors—the video sensor, the sound sensor, and the control sensor—are not activated in Fig. 1.

To perform the context reasoning, firstly, we represent abbreviations for the motion sensor, *Ms*, the video sensor *Vs*, the sound sensor *Ss*, the light sensor *Ls*, the control sensor *Cs*, and the device sensor *Ds* in Fig. 1. We then represent a piece of evidence on each sensor as a mass function. We have

$$m_{Ms}(\{Ms\})=1 \qquad m_{Vs}(\{\neg Vs\})=1$$
$$m_{Ss}(\{\neg Ss\})=1 \qquad m_{Ls}(\{Ls\})=1$$
$$m_{Cs}(\{\neg Cs\})=1 \qquad m_{Ds}(\{Ds\})=1$$

Second, we apply an error rate *r* to each sensor using to obtain credibility. Within our scenario, we assume that the motion sensor *Ms* has a 15% error rate, the video and sound sensor (*Vs* and *Ss*) have a 20% error rate, and the action detecting sensors (*Ls*, *Cs*, and *Ds*) have a 5% error rate when they are manufactured. In addition, we apply a multivalued mapping to represent the belief level of a context attribute by translating a mass function in [1]. We utilize abbreviations for the infrared *I*, the camera *C*, the audio *A*, the light *L*, remote controller *R*, and the second device *D*. We then aggregate context attributes and translate them into two related context states. A mass function on *M*, *C*, and *A* are translated onto the context state 1 (*CS*1), and a mass function on *L*, *R*, and *D* is translated onto the context state 2 (*CS*2).

Both *CS*1 and *CS*2 are used for determining the relevant activities of the patient, i.e.,

$$m1_{CS1}(\{CS1\})=m_I(\{I\})=m^r_{Ms}(\{Ms\})=0.85$$
$$m1_{CS1}(\{CS1,\neg CS1\})=m_I(\{I,\neg I\})=m^r_{Ms}(\{Ms,\neg Ms\})=0.15$$
$$m2_{CS1}(\{\neg CS1\})=m_C(\{\neg C\})=m^r_{Vs}(\{\neg Vs\})=0.80$$
$$m2_{CS1}(\{CS1,\neg CS1\})=m_C(\{C,\neg C\})=m^r_{Vs}(\{Vs,\neg Vs\})=0.20$$
$$m3_{CS1}(\{\neg CS1\})=m_A(\{\neg A\})=m^r_{Ss}(\{\neg Ss\})=0.80$$
$$m3_{CS1}(\{CS1,\neg CS1\})=m_A(\{A,\neg A\})=m^r_{Ss}(\{Ss,\neg Ss\})=0.20$$
$$m1_{CS2}(\{CS2\})=m_L(\{L\})=m^r_{Ls}(\{Ls\})=0.95$$
$$m1_{CS2}(\{CS2,\neg CS2\})=m_L(\{L,\neg L\})=m^r_{Ls}(\{Ls,\neg Ls\})=0.05$$
$$m2_{CS2}(\{\neg CS2\})=m_R(\{\neg R\})=m^r_{Cs}(\{\neg Cs\})=0.95$$
$$m2_{CS2}(\{CS2,\neg CS2\})=m_R(\{R,\neg R\})=m^r_{Cs}(\{Cs,\neg Cs\})=0.05$$
$$m3_{CS2}(\{CS2\})=m_D(\{D\})=m^r_{Ds}(\{Ds\})=0.95$$
$$m3_{CS2}(\{CS2,\neg CS2\})=m_D(\{D,\neg D\})=m^r_{Ds}(\{Ds,\neg Ds\})=0.05$$

Third, we sum up a context state by adapting a different static weighting factor to each context attribute involved in the context context state. We assume that the weighting factor of *CS*1 consists of I (20%), *C* (30%), and *A* (50%), and the weighting factor of *CS*2 consists of *L* (10%), *R* (60%), and *D* (30%). We have

$$m_{CS1}(\{CS1\})=(0.2)(m1_{CS1})=0.17$$
$$m_{CS1}(\{\neg CS1\})=(0.3)(m2_{CS1})+(0.5)(m3_{CS1})=0.64$$
$$m_{CS1}(\{CS1,\neg CS1\})=(0.2)(m1_{CS1})+(0.3)(m2_{CS1})+(0.5)(m3_{CS1})=0.19$$
$$m_{CS2}(\{CS2\})=(0.1)(m1_{CS2})+(0.3)(m3_{CS2})=0.38$$
$$m_{CS2}(\{\neg CS2\})=(0.6)(m2_{CS2})=0.57$$
$$m_{CS2}(\{CS2,\neg CS2\})=(0.1)(m1_{CS2})+(0.6)(m2_{CS2})+(0.3)(m3_{CS2})=0.05$$

We assume that both *CS*1 and *CS*2 can be used for inferring the concentrated (*CC*) and distracted (*DD*) situations of the client. In this paper, we calculate two mass functions $m1_{CC}$ and $m2_{CC}$ to identify the *CC* situation of the client, i.e.,

$$m1_{CC}(\{CC\})=m_{CS1}(\{CS1\})=0.17$$
$$m1_{CC}(\{\neg CC\})=m_{CS1}(\{\neg CS1\})=0.64$$
$$m1_{CC}(\{CC,\neg CC\})=m_{CS1}(\{CS1,\neg CS1\})=0.19$$
$$m2_{CC}(\{CC\})=m_{CS2}(\{CS2\})=0.38$$
$$m2_{CC}(\{\neg CC\})=m_{CS2}(\{\neg CS2\})=0.57$$
$$m2_{CC}(\{CC,\neg CC\})=m_{CS2}(\{CS2,\neg CS2\})=0.05$$

Fourth, by combining two sources as described in [1], we achieve the conjunctive consensus with the conflicting mass (k_{12}). We then redistribute the partial conflicting mass using as follows:

$$\mathrm{M}=\begin{pmatrix} \mathrm{m}_1(CC) & \mathrm{m}_1(\neg CC) & \mathrm{m}_1(CC\cup\neg CC) \\ \mathrm{m}_2(CC) & \mathrm{m}_2(\neg CC) & \mathrm{m}_2(CC\cup\neg CC) \end{pmatrix}$$
$$m_{12}(\varnothing)=0 \qquad m_{12}(CC)=0.1453$$
$$m_{12}(\neg CC)=0.5051 \qquad m_{12}(CC\cup\neg CC)=0.0095$$
$$k_{12}=m_{12}(CC\cap\neg CC)=\mathrm{m}_1(CC)\mathrm{m}_2(\neg CC)+\mathrm{m}_1(\neg CC)\mathrm{m}_2(CC)=0.3401$$
$$m_{DS}(CC)=m_1\oplus m_2(CC)=\frac{1}{1-k_{12}}m_{12}(CC)=0.2202$$
$$m_{DS}(\neg CC)=\frac{1}{1-k_{12}}m_{12}(\neg CC)=0.7654$$
$$m_{DS}(CC\cup\neg CC)=\frac{1}{1-k_{12}}m_{12}(CC\cup\neg CC)=0.0144$$

After achieving the value of k_{12}, the partial conflicting mass $m_1(CC)m_2(\neg CC)$ is distributed to *CC* and $\neg CC$ proportionaly with the masses $m_1(CC)$ and $m_2(\neg CC)$ assigned to *CC* and $\neg CC$, respectively. We suppose that x_1 and y_1 is the conflicting mass to be redistributed to *CC* and $\neg CC$, respectively, to calculate the first partial conflicting mass $m_1(CC)m_2(\neg CC)$ as follows:

$$\frac{x_1}{m_1(CC)} = \frac{y_1}{m_2(\neg CC)} = \frac{x_1 + y_1}{(0.17)+(0.57)} = 0.1309$$

Thus, $x_1 = 0.0223$, $y_1 = 0.0746$.

In addition, the partial conflicting mass $m_2(CC)m_1(\neg CC)$ is proportionally distributed to CC and $\neg CC$ with the masses $m_2(CC)$ and $m_1(\neg CC)$ assigned to CC and $\neg CC$, respectively. We suppose that x_2 and y_2 is the conflicting mass to be redistributed to CC and $\neg CC$, respectively, to calculate the second partial conflicting mass $m_2(CC)m_1(\neg CC)$. We have

$$\frac{x_2}{m_2(CC)} = \frac{y_2}{m_1(\neg CC)} = \frac{x_2 + y_2}{(0.38)+(0.64)} = 0.2384$$

Thus, $x_2 = 0.0906$, $y_2 = 0.1526$.

We can obtain two results of the redistribution for each corresponding set CC and $\neg CC$, respectively. We then obtain the result of the PCR5 rule as follows:

$$m_{PCR5}(CC) = m_{12}(CC) + x_1 + x_2 = 0.2582$$
$$m_{PCR5}(\neg CC) = m_{12}(\neg CC) + y_1 + y_2 = 0.7323$$
$$m_{PCR5}(CC \cup \neg CC) = m_{12}(CC \cup \neg CC) + 0 = 0.0095$$

Finally, we calculate the belief and uncertainty level of the concentrated context with two combination rules using (1), (2), and (13) described in [1]. We then calculate the maximum of pignistic probability with a decision rule, i.e.,

$$Bel(\{CC\}) = m_{DS}(\{CC\}) = 0.2202$$
$$Pl(\{CC\}) = m_{DS}(\{CC\}) + m_{DS}(\{CC, \neg CC\}) = 0.2346$$
$$Pl(\{CC\}) - Bel(\{CC\}) = m_{DS}(\{CC, \neg CC\}) = 0.0144$$

$$Bel(\{CC\}) = m_{PCR5}(\{CC\}) = 0.2582$$
$$Pl(\{CC\}) = m_{PCR5}(\{CC\}) + m_{PCR5}(\{CC, \neg CC\}) = 0.2677$$
$$Pl(\{CC\}) - Bel(\{CC\}) = m_{PCR5}(\{CC, \neg CC\}) = 0.0095$$

$$P_{DS}(\{CC\}) = m_{DS}(\{CC\}) + \frac{1}{2} m_{DS}(\{CC, \neg CC\}) = 0.2274$$

$$P_{PCR5}(\{CC\}) = m_{PCR5}(\{CC\}) + \frac{1}{2} m_{PCR5}(\{CC, \neg CC\}) = 0.2629$$

In this scenario, we simply know that the mass of ignorance committed by the PCR5 rule ($m_{PCR5}(CC \cup \neg CC) = 0.0095$) is less than that of Dempster's rule ($m_{DS}(CC \cup \neg CC) = 0.0144$), because Dempster's combination rule takes the total conflicting mass and then redistributes it to all nonempty sets, even those not involved in the conflict. In addition, when we compare the confidence level of the two cases, the maximum of pignistic probability of the PCR5 rule ($P_{PCR5}(\{CC\}) = 0.2629$) is higher than that of Dempster's rule ($P_{DS}(\{CC\}) = 0.2274$), since PCR5 rule redistributes the partial conflicting mass to both positive and negative results of mass distributions concurrently. As a result, it is shown that the DSmT approach based on PCR5 rule is better than the DST approach based on Dempster's rule.

IV. Conclusions

In this paper, we demonstrate an Evidential Fusion Network (EFN) based context reasoning for smart media service. For this we conduct the context classification and state-space based context modelling. Then, we perform the static evidential fusion process (SEFP) to obtain a higher confidence level of contextual information. According to the results, the DSmT approach is better than the DST approach. In the future, we will improve the quality of a context by considering dynamic weighting factors, because correctly designing the quality of a context is an important factor for improving the contextual information of the client.

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