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Sensor Data Fusion using DSm Theory for Activity Recognition under Uncertainty in Home-based Care

Hyun Lee Jae Sung Choi Ramez Elmasri
Computer Science and Engineering
University of Texas at Arlington
Arlington, TX, 76019
{hlee, jschoi, and elmasri}@uta.edu

Abstract

Reliable contextual information of remotely monitored patients should be generated to prevent hazardous situations and to provide pervasive services in home-based care. This is difficult for several reasons. First, low level data obtained from heterogeneous sensors have different degrees of uncertainty. Second, generated contexts can be corrupted or conflicted even if they are acquired by simultaneous operations. In this paper, we utilize Dezert-Smarandache Theory (DSmT) as an evidence fusion approach to reduce ambiguous or imperfect information then to get higher belief levels in the data fusion process of contextual information. To analyze the improvement of DSmT fusion process, we compare DSmT with Dempster-Shafer Theory (DST) using PCR5 rule of combination and Dempster's rule of combination respectively.

1. Introduction

A wide range of pervasive computing technologies aim to provide pervasive services to patients using intelligent embedded systems in smart home-based care. A Pervasive Healthcare Monitoring System (PHMS) [3] enables continuous healthcare monitoring without spatial-temporal limitations and can provide methods for independent safe living and remote disease management by recognizing the activities of the patient in real time. A key approach of the PHMS is that reliable contextual information about a patient should be generated to prevent particular hazardous situations of the patient [7]. However, a higher confidence level in the generated contexts is difficult to produce, since multiple sensors may not provide reliable information due to faults, operational tolerance levels, or corrupted data even though they are acquired by simultaneous operations. For instance, unpredictable malfunctions of sensors frequently happen in heterogeneous sensor environments. They cause invalid readings then change the state of the context, which is associated with the patient, incorrectly. Some sensor readings also give information about context only at an abstract level, which can include uncertainty to some extent. It is difficult to make a context reasoning for inferring the activities of the patient directly. Moreover, if data obtained from sensors are corrupted or conflicted, the activities of the patient are more ambiguous. In this paper, we aim to reduce ambiguous or imperfect contextual information using Dezert-Smarandache Theory (DSmT) [1] of evidence as a sensor data fusion technique to get a reliable activity recognition under uncertain or conflicting situations in smart home-based care applications.

Among sensor data fusion techniques, Bayesian methods [8], [9] and evidence theories such as Dempster-Shafer Theory (DST) [12], [2] are commonly used to handle the degree of uncertainty in fusion processes. As a generalized probabilistic approach, DST, which considers upper and lower bounds of probability, has some distinct features when compared with Bayesian theory. This is because it represents the ignorance caused by the lack of information and aggregates the belief when new evidence is accumulated [2]. This is a useful feature to manage the degree of uncertainty, which has not been accommodated for. However, the DST approach also has a low confidence to trust results of Dempster's combination rule when conflict between sources becomes important [1]. In this paper, DSmT approach, which overcomes drawbacks of Dempster's combination rule and extends the domain of application of the belief functions, is used as a sensor data fusion technique.

The rest of paper is organized as follows. In section 2, we explain requirements for activity recognition under uncertainty in home-based care. The basics of evidence theories and two combination rules are introduced in section 3. We infer the activities of a patient based on the applied scenario then compare DST approach with DSmT approach

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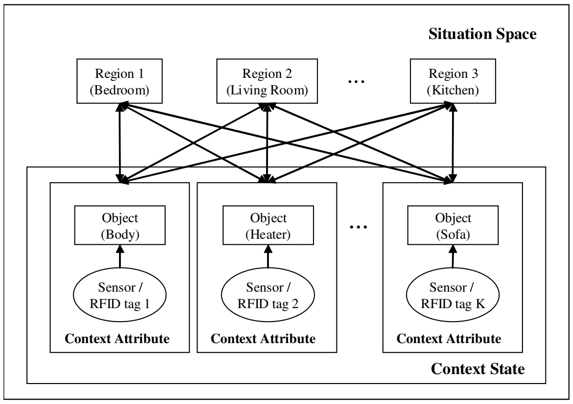

Figure 1. A hierarchical interrelationships between sensors, related contexts, and relevant situation spaces based on a state-space modeling

for analyzing the results of two cases in section 4. Then we conclude the paper in section 5.

2. Requirements for Activity Recognition under Uncertainty in Home-based Care

2.1. Characteristics of Sensors

A PHMS [3] can utilize several types of sensors such as medical body sensors, environmental sensors and actuators, location sensors, and time stamps. A PHMS combines sensed data to recognize activities of patients depending on context classifications then supports pervasive services to patients based on pre-defined rules. However, each sensor is unable to directly identify the situation of patients. This is because the complexity of context classifications or pre-defined rules is very high. An exceptional error case also frequently happen in the PHMS operation. Thus, we assume that each sensor has a binary value such as 1 (active) and 0 (inactive) in this paper. Whenever the state of a certain context associated with a sensor is changed, the value of a sensor is changed from 0 to 1 or from 1 to 0. For instance, a medical body sensor has a threshold that indicates the emergency status of a patient if a sensor value is over the pre-defined threshold. An environmental sensor also has a threshold based on pre-defined rules to operate the actuator. A location detecting sensor operates if a patient is within the range of the detection area. Hence we can simply express the status of each sensor as a frame: $\Theta = \{Threshold_{over}, Threshold_{not-over}\} = \{1, 0\}$.

2.2. State-Space based Modeling

For inferring the situation of a patient under uncertainty, we apply a formal model, the state-space based model [6], that represents perceived contexts of the activities of a patient. A state-space based model consists of three steps as follows.

A **context attribute**, denoted by α_i, is defined as any type of data that is used in the process of inferring situations. A context attribute is often associated with sensors, virtual or physical, where the values of the sensor readings denote the context attribute value at a given time t, denoted by α_i^t. These sensors are unable to directly identify situations on their own, but they can provide a binary value as a context attribute.

A **context state** describes the current state of the application in relation to chosen context, and is denoted by a vector S_i. It is a collection of *N* context attribute values that are used to represent a specific state of the system at time *t*. Hence a context state is denoted as $S_i^t = (\alpha_1^t, \alpha_2^t, \ldots, \alpha_N^t)$, where each value α_i^t corresponds to the value of an attribute α_i at time *t*. In this paper, whenever the activity is recognized by a certain binary sensor, the value of the sensor changes to 1 from 0 then the context state changes the current state depending on the aggregation of the state of some context attributes having 1 value.

A real-life monitoring situation is represented by a **situation space**. It is a collection of regions of attribute values corresponding to some pre-defined situations and denoted by a vector space $R_i = (\alpha_1^R, \alpha_2^R, \ldots, \alpha_M^R)$, that consists of *M* acceptable regions for these attributes. An acceptable region α_i^R is defined as a set of elements *V* that satisfies a predicate *P*, i.e., $\alpha_i^R = V \setminus P(V)$. A particular activity can be performed or associated with a certain region in the intelligent home.

Finally, we apply interrelationships among sensors(α_i^t), related contexts(S_i^t), and relevant activities within a region(R_i) for making the state-space based model as shown in Figure 1.

2.3. Quality of Data

In home-based care applications, some types of information are more important than others for recognizing the situation/activity of a patient. For example, a high body temperature may be a strong indicator of a general sickness while other attributes such as the values of environmental sensors or location sensors may not be so important for inferring the particular situation. To model the variation in the importance of context attributes which recognize the situation/activity of a patient, we define the quality of data, which assigns weights to context attributes. These weighting factors reflect the importance of each attribute at any given time and location. Hence we can define the quality of data as below.

Quality of Data: Given a context attribute *i*, a quality of data ψ_i associates weights $\omega_1, \omega_2, \ldots, \omega_N$ with combined attributes of values $\alpha_1^t + \alpha_1^R, \alpha_2^t + \alpha_2^R, \ldots, \alpha_N^t + \alpha_N^R$ of *i*, respectively, where $\sum_{j=1}^{N} \omega_j = 1$. A weight $\omega_j \in (0, 1]$ represents the relative importance of a context attribute α_j compared to other attributes in the given time *t* and region *R*.

3. Basics on DST and DSmT

3.1. Basics of Evidential Theory

An evidential theory such as DST that is further extended by Shafer [10], is a generalization of traditional probability, which allows us to better quantify uncertainty. Shafer's model, denoted here by $M^0(\Theta)$, consider $\Theta = \{\theta_1, \cdots, \theta_n\}$ as a finite set of *n* exhaustive and exclusive elements representing the possible states of the sensor. In DST, the set, denoted by Θ, is called the ***frame of discernment*** of the sensor. For instance, $\{1, 0\}$ is the frame of discernment for sensors in which one(1) represents the value of sensor is over the threshold and zero(0) represents the value of sensor is not over the threshold. In the DSmT framework [1], the free DSm model, denoted by $M^f(\Theta)$ where $\Theta = \{\theta_1, \cdots, \theta_n\}$, is only assumed to be a finite set of *n* exhaustive elements. If one considers θ_1 and θ_2 are truly exclusive (i.e., $\theta_1 \cap \theta_2 = \emptyset$), then the model is said to be *hybrid*. When we include all exclusivity constraints on elements of Θ, $M^f(\Theta)$ is equal to $M^0(\Theta)$. This means that DST model is a particular case of DSm hybrid model. Between the free DSm model and the Shafer's model, there exists a wide class of fusion problems represented in terms of DSm hybrid model where Θ involves both fuzzy continuous hypothesis and discrete hypothesis.

In DST, the *power set* of Θ, denoted 2^Θ, is defined by the rules 1, 2, and 3 given below based on Θ and $M^0(\Theta)$. In DSmT, the *hyper-power set*, denoted D^Θ, is defined by the rules 4, 5, and 6 without additional assumption on Θ but the exhaustivity of its elements.

1) $\emptyset, \theta_1, \cdots, \theta_n \in 2^\Theta$.

2) If $\theta_1, \theta_2 \in 2^\Theta$, then $\theta_1 \cup \theta_2$ belong to 2^Θ.

3) No other elements belong to 2^Θ, except those obtained by using rules 1) or 2).

4) $\emptyset, \theta_1, \cdots, \theta_n \in D^\Theta$.

5) If $\theta_1, \theta_2 \in D^\Theta$, then $\theta_1 \cap \theta_2$ and $\theta_1 \cup \theta_2$ belong to D^Θ.

6) No other elements belong to D^Θ, except those obtained by using rules 4) or 5).

When Shafer's model ($M^0(\Theta)$) holds, D^Θ reduces to the classical power set 2^Θ. Without loss of generality, the general set, denoted G^Θ, on which will be defined the basic belief assignments is equal to 2^Θ if Shafer's model ($M^0(\Theta)$) is adopted. Whereas $G^\Theta = D^\Theta$ if DSm model is preferred depending on the nature of the problem.

Generally, many factors surrounding the sensors have an impact on the quality of the observation of the sensor. Thus, evidential theory uses a number in the range [0,1] to represent the degree of belief in the observation. The distribution of a unit of belief over the frame (Θ) is called ***evidence***. Then a ***mass function*** $m(.) : G^\Theta \to [0, 1]$ associated to a given source, say *s*, of evidence is defined to represent the distribution of belief and to satisfy two conditions:

$$m_s(\emptyset) = 0 \qquad \text{and} \qquad \sum_{X \in G^\Theta} m_s(X) = 1 \tag{1}$$

X is a subset of Θ and $m_s(X)$ is the general basic belief assignment (gbba) of *X* committed by the source *s*.

In evidential theory, a range of probability rather than a single probabilistic number is used to represent uncertainty of the sensor. The lower and upper bounds of the probability are called the ***Belief (Bel)*** and ***Plausibility (Pl)*** respectively. Thus, *Bel* and *Pl* of any proposition $X \in G^\Theta$ are defined as:

$$Bel(X) \triangleq \sum_{\substack{Y \subseteq X \\ Y \in G^\Theta}} m(Y) \quad \text{and} \quad Pl(X) \triangleq \sum_{\substack{Y \cap X = \emptyset \\ Y \in G^\Theta}} m(Y) \tag{2}$$

Based on eq. (2), *Bel* shows the degree of belief to which the evidence supports *X*. Whereas *Pl* shows the degree of belief to which the evidence fails to refute *X*.

3.2. Evidential Operations

For inferring the situation/acitivity along evidential networks, ***reliability discounting*** methods which transform beliefs of each source are used to reflect the sensor's credibility, in terms of *discount rate* r $(0 \leq r \leq 1)$. The discount mass function is defined as:

$$m^r(X) = \begin{cases} (1-r)m(X) & X \subset \Theta \\ r + (1-r)m(\Theta) & X = \Theta \end{cases} \tag{3}$$

where the source is absolutely reliable *(r = 0)*, the source is reliable with a discount rate r $(0 < r < 1)$, and the source is completely unreliable *(r = 1)*.

In evidential theory, a ***multi-valued mapping*** is used to reflect the relationship between two frames of discernment (Θ_A, Θ_B) which represent the evidence to the same problem with different views. Thus, a multi-valued mapping Γ describes a mapping function $\Gamma : \Theta_A \leftarrow 2^{\Theta_B}$ by assigning a subset $\Gamma(e_i)$ of Θ_B to each element e_i of Θ_A. Based on the multi-valued mapping, ***translation*** can be used to determine the impact of evidence originally appearing on a frame of discernment on elements of a compatibly related frame of discernment. For example, suppose that Θ_A carries a mass function *m*, the translated mass function over the compatibly related Θ_B is defined as:

$$m'(B_j) = \sum_{\Gamma(e_i)=B_j} m(e_i) \tag{4}$$

where $e_i \in \Theta A, B_j \subseteq \Theta_B$, and $\Gamma : \Theta_A \to 2^{\Theta_B}$ is a multi-valued mapping. Sometimes, the relationship between an element e_i of Θ_A and a subset B_{ij} of Θ_B may be uncertain. Thus, an evidential mapping in [4] assigns probabilities to an elements e_i of Θ_A instead of a set of subsets to represent such uncertain relationships. A piece of evidence on Θ_A is also propagated to Θ_B through an evidential mapping when the relationship is uncertain. Translation is just a special case of propagation, in which relationships between evidence space Θ_A and hypothesis space Θ_B are certain.

Finally, belief distributions on the same frame in DST can be combined by several independent sources of evidence using Dempster's combination rule. The Proportional Conflict Redistribution rule no. 5 (PCR5) [5] is currently used in DSmT as a combination rule. No matter if the conflicting mass is big or small, PCR5 mathematically does a better redistribution of the conflicting mass than other rules since PCR5 goes backwards on the tracks of the conjunctive rule. For this reason, we consider PCR5 as a combination rule in DSmT. We also compare PCR5 with Dempster's rule used in DST. Both rules are mainly based on the conjunctive consensus operator defined for two-sources cases by:

$$m_{12}(X) = \sum_{\substack{X_1,X_2 \in G^\Theta \\ X_1 \cap X_2 = X}} m_1(X_1) m_2(X_2) \tag{5}$$

The totlal conflicting mass drawn from two sources, denoted k_{12}, is defined as:

$$k_{12} = \sum_{\substack{X_1,X_2 \in G^\Theta \\ X_1 \cap X_2 = \emptyset}} m_1(X_1) m_2(X_2) = \sum_{\substack{X_1,X_2 \in G^\Theta \\ X_1 \cap X_2 = \emptyset}} m(X_1 \cap X_2) \tag{6}$$

Based on eq. (6), we know that the total conflicting mass is the sum of partial conflicting masses. If k_{12} is close to 1, two sources are almost in total conflict. Whereas if k_{12} is close to 0, the two sources are not in conflict.

3.3. DST Combination Rule

In DST, the Dempster's rule of combination of $m_1(.)$ and $m_2(.)$ is obtained based on Shafer's model ($m^0(\Theta)$) and two independent sources $m_1(.)$ and $m_2(.)$. In this case, $G^\Theta = 2^\Theta$ then $m_{DS}(\emptyset) = 0$ and $\forall (X \neq \emptyset) \in 2^\Theta$ by:

$$m_{DS}(X) = \frac{1}{1-k_{12}} m_{12}(X), \quad (k_{12} \neq 1) \tag{7}$$

where $m_{12}(X)$ and k_{12} are defined by eq. (5) and eq. (6) respectively. Dempster's rule can be directly extended for the combination of *N* independent and equally reliable sources of evidence.

3.4. DSmT Combination Rule

In DSmT, PCR5 is used as a combination rule in this paper. PCR5 redistributes the partial conflicting mass only to the elements involved in that partial conflict. First, PCR5 calculates the conjunctive rule of the belief masses of sources. Second, PCR5 calculates the total or partial conflicting masses. And last, PCR5 redistributes the conflicting masses proportionally to non-empty sets involved in the model according to all integrity constraints.

PCR5 combination rule for two sources is defined by [11]: $m_{PCR5}(\emptyset) = 0$ and $\forall (X \neq \emptyset) \in G^\Theta$

$$m_{PCR5}(X) = m_{12}(X) + \sum_{\substack{Y \in G^\Theta \setminus \{X\} \\ c(X \cap Y) = \emptyset}} [\frac{m_1(X)^2 m_2(Y)}{m_1(X) + m_2(Y)} + \frac{m_2(X)^2 m_1(Y)}{m_2(X) + m_1(Y)}] \tag{8}$$

where m_{12} is defined by eq. (5) and all denominators such as $m_1(X) + m_2(Y)$ and $m_2(X) + m_1(Y)$ are differ from zero(0). If a denominator is zero, that fraction is discarded. All sets in the formula are also in canonical forms. Thus, *c(X)* is the canonical form of *X*. (i.e., if $X = (A \cap B) \cap (A \cup B \cup C)$ then $c(X) = (A \cap B)$).

4. Comparative Analysis

4.1. Applied Scenario

Many ambiguous situations can happen in home-based care applications. However, we simply assume two situations in this paper. A patient or an elderly person is "sleeping" or "fainting" on the sofa when the lighting and the heater of the living room are turned on and the pressure sensor attached on the sofa becomes active. In addition, medical body sensors (blood pressure, body temperature, and respiratory rate) are operated to check the status of the person. Based on these simplified two cases, we can derive evidential networks as shown in Figure 2. We can then find out more closely correct situations through evidential inference. In Figure 2, each state (sensors, objects, and contexts) is represented by the evidential forms such as a frame of discernment (Θ) as shown in Table 1. All relations between sensors, objects, and the related contexts are also represented by a multi-valued mapping as shown in Table 2.

4.2. Situation (Activity) Inference

Within a scenario, an evidence of the sensor operation in a context attribute may deduce objects in detail, or be summed up onto a context state by adapting a different quality of data. That is then translated into the relevant situation

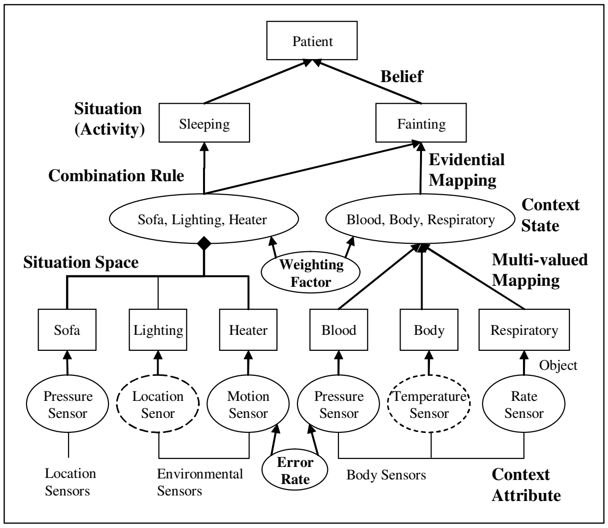

Figure 2. An example of "sleeping" or "fainting" situation inference based on the evidential forms

Table 1. Examples of frames of discernment

Name	Type	Frame of discernment
Pressure	Sensor	$\{Threshold_{\uparrow}, \neg Threshold_{\downarrow}\}$
Sofa	Context	$\{Active, Inactive\}$
Sleeping	Situation	$\{Sleeping, Fainting\}$

recognition by applying an evidential mapping. On a situation recognition step, several belief distributions can be combined by different rules of combination. Among them, we use Dempster's rule of combination and PCR5 rule of combination. Based on the simplified scenario, inference procedures are followed by some steps of evidential operations.

First, we represent an evidence on each sensor as a mass function. We use the abbreviations *Pressure sensor = Ps*, *Location sensor = Ls, Motion sensor = Ms, Blood Pressure sensor = BPs, Temperature sensor = Ts*, and *Rate sensor = Rs*. According to Figure 2, a mass function on each sensor is represented by:

$$m_{Ps}(\{Ps\}) = 1; m_{Ls}(\{\neg Ls\}) = 1; m_{Ms}(\{Ms\}) = 1;$$
$$m_{BPs}(\{BPs\}) = 1; m_{Ts}(\{\neg Ts\}) = 1; m_{Rs}(\{Rs\}) = 1;$$

Second, evidences on each sensor are discounted since each sensor has different discount (error) rates. As a discounting rate, we assume that medical body sensors have 5% error rate, location sensors have 10% error rate, and environmental sensors have 20% error rate. Discounted mass functions can be calculated to get sensor's credibility using eq. (3):

Table 2. Multi-valued mapping relationships

Relationship	Multi-valued mapping
Pressure(Ps)→Sofa (S)	$\{Ps\} \rightarrow \{S\}$; $\{\neg Ps\} \rightarrow \{\neg S\}$; $\{(Ps, \neg Ps)\} \rightarrow \{(S, \neg S)\}$;
S →(S, Heater (H))	$\{S\} \rightarrow \{(S, H)\}$; $\{\neg S\} \rightarrow \{\neg(S, H)\}$; $\{(S, \neg S)\} \rightarrow$ $\{(S, H), \neg(S, H)\}$;
(S, H)→Sleeping (Sl)	$\{(S, H)\} \rightarrow \{Sl\}$; $\{\neg(S, H)\} \rightarrow \{\neg Sl\}$; $\{(S, H), \neg(S, H)\} \rightarrow$ $\{(Sl), \neg(Sl)\}$;
(Sl)→Activity (A)	$\{Sl\} \rightarrow \{A\}$; $\{\neg Sl\} \rightarrow \{\neg A\}$; $\{(Sl, \neg Sl)\} \rightarrow \{(A, \neg A)\}$;

$$m^r_{Ps}(\{Ps\}) = 0.90; m^r_{Ps}(\{Ps, \neg Ps\}) = 0.10;$$
$$m^r_{Ls}(\{\neg Ls\}) = 0.80; m^r_{Ls}(\{Ls, \neg Ls\}) = 0.20;$$
$$m^r_{Ms}(\{Ms\}) = 0.80; m^r_{Ms}(\{Ms, \neg Ms\}) = 0.20;$$
$$m^r_{BPs}(\{BPs\}) = 0.95; m^r_{BPs}(\{BPs, \neg BPs\}) = 0.05;$$
$$m^r_{Ts}(\{\neg Ts\}) = 0.95; m^r_{Ts}(\{Ts, \neg Ts\}) = 0.05;$$
$$m^r_{Rs}(\{Rs\}) = 0.95; m^r_{Rs}(\{Rs, \neg Rs\}) = 0.05;$$

Third, we apply a multi-valued mapping to represent the relationship between sensors and associated objects by translating mass functions. In other words, the belief levels of a context attribute are represented by a multi-valued mapping. We use the abbreviations *Sofa = S, Lighting = L, Heater = H, Blood = Bl, Body = B,* and *Respiratory = R*.

$$m_S(S) = m^r_{Ps}(\{Ps\}) = 0.90;$$
$$m_S(\{S, \neg S\}) = m^r_{Ps}(\{Ps, \neg Ps\}) = 0.10;$$
$$m_L(\neg L) = m^r_{Ls}(\{\neg Ls\}) = 0.80;$$
$$m_L(\{L, \neg L\}) = m^r_{Ls}(\{Ls, \neg Ls\}) = 0.20;$$
$$m_H(H) = m^r_{Ms}(\{Ms\}) = 0.80;$$
$$m_H(\{H, \neg H\}) = m^r_{Ms}(\{Ms, \neg Ms\}) = 0.20;$$
$$m_{Bl}(Bl) = m^r_{BPs}(\{BPs\}) = 0.95;$$
$$m_{Bl}(\{Bl, \neg Bl\}) = m^r_{BPs}(\{BPs, \neg BPs\}) = 0.05;$$
$$m_B(\neg B) = m^r_{Ts}(\{\neg Ts\}) = 0.95;$$
$$m_B(\{B, \neg B\}) = m^r_{Ts}(\{Ts, \neg Ts\}) = 0.05;$$
$$m_R(R) = m^r_{Rs}(\{Rs\}) = 0.95;$$
$$m_R(\{R, \neg R\}) = m^r_{Rs}(\{Rs, \neg Rs\}) = 0.05;$$

Fourth, context attributes are aggregated then translated to the related context states by using a multi-valued mapping. Mass functions on *"Sofa", "Lighting",* and *"Heater"* are aggregated then translated onto Context State 1 *(CS1)* used for determining "sleeping" or "fainting" situation. Mass functions on *"Blood", "Body",* or *"Respiratory"* are aggregated then translated onto Context State 2 *(CS2)* used for only determining "fainting" situation.

$m1_{CS1}(\{CS1\}) = m_S(\{S\}) = 0.90;$
$m1_{CS1}(\{CS1, \neg CS1\}) = m_S(\{S, \neg S\}) = 0.10;$
$m2_{CS1}(\{\neg CS1\}) = m_L(\{\neg L\}) = 0.80;$
$m2_{CS1}(\{CS1, \neg CS1\}) = m_L(\{L, \neg L\}) = 0.20;$
$m3_{CS1}(\{CS1\}) = m_H(\{H\}) = 0.80;$
$m3_{CS1}(\{CS1, \neg CS1\}) = m_H(\{H, \neg H\}) = 0.20;$
$m1_{CS2}(\{CS2\}) = m_{Bl}(\{Bl\}) = 0.95;$
$m1_{CS2}(\{CS2, \neg CS2\}) = m_S(\{Bl, \neg Bl\}) = 0.05;$
$m2_{CS2}(\{\neg CS2\}) = m_B(\{\neg B\}) = 0.95;$
$m2_{CS2}(\{CS2, \neg CS2\}) = m_B(\{B, \neg B\}) = 0.05;$
$m3_{CS2}(\{CS2\}) = m_R(\{R\}) = 0.95;$
$m3_{CS2}(\{CS2, \neg CS2\}) = m_R(\{R, \neg R\}) = 0.05;$

Fifth, each context state is summed up by adapting a different quality of data. Within context state 1, we assume that the weighting factor of *"S" = 0.6, "L" = 0.2,* and *"H" = 0.2*. Within context state 2, we assume that the weighting factor of *"Bl" = 0.3, "B" = 0.3,* and *"R" = 0.4*.

$m_{CS1}(\{CS1\}) =$
$\{((0.6) \times m1_{CS1}) + ((0.2) \times \{m3_{CS1}\})\}(\{CS\}) = 0.7;$

$m_{CS1}(\{\neg CS1\}) = \{((0.2) \times m2_{CS1})\}(\{\neg CS1\}) = 0.16;$

$m_{CS1}(\{CS1, \neg CS1\}) = \{((0.6) \times m1_{CS1}) + ((0.2) \times \{m2_{CS1} + m3_{CS1}\})\}(\{CS1, \neg CS1\}) = 0.14;$

$m_{CS2}(\{CS2\}) =$
$\{((0.3) \times m1_{CS2})\} + ((0.4) \times \{m3_{CS2}\})(\{CS\}) = 0.665;$

$m_{CS2}(\{\neg CS2\}) = \{((0.3) \times m2_{CS2})\}(\{\neg CS2\}) = 0.285;$

$m_{CS2}(\{CS2, \neg CS2\}) = \{((0.3) \times m1_{CS2}) + ((0.3) \times \{m2_{CS2}\} + ((0.4) \times \{m3_{CS2}\}\}(\{CS2, \neg CS2\}) = 0.05;$

And last, one context state *(CS1)* is only used for inferring "sleeping" *(Sl)* situation. Two context states (*CS1* and *CS2*) are used for inferring "fainting" *(F)* situation.

$m_{Sl}(\{Sl\}) = m_{CS1}(\{CS1\}) = 0.7;$
$m_{Sl}(\{\neg Sl\}) = m_{CS1}(\{\neg CS1\}) = 0.16;$
$m_{Sl}(\{Sl, \neg Sl\}) = m_{CS1}(\{CS1, \neg CS1\}) = 0.14;$

$m1_F(\{F\}) = m_{CS1}(\{CS1\}) = 0.7;$
$m1_F(\{\neg F\}) = m_{CS1}(\{\neg CS1\}) = 0.16;$
$m1_F(\{F, \neg F\}) = m_{CS1}(\{CS1, \neg CS1\}) = 0.14;$

$m2_F(\{F\}) = m_{CS2}(\{CS2\}) = 0.665;$
$m2_F(\{\neg F\}) = m_{CS2}(\{\neg CS2\}) = 0.285;$
$m2_F(\{F, \neg F\}) = m_{CS2}(\{CS2, \neg CS2\}) = 0.05;$

For inferring "sleeping" situation, we just calculate m_{Sl} mass function. However, for inferring "fainting" situation, we should calculate two mass functions $m1_F$ and $m2_F$. In this case, two independent sources are combined to achieve the consensus by using Dempster's rule of combination or PCR5 rule of combination.

4.3. Applying Dempster's rule of combination

To achieve the conjunctive consensus with the conflicting mass (k_{12}), we first apply the results of last steps into eq. (5) and eq. (6).

For instance,

$$\mathbf{M} = \begin{pmatrix} m_1(F) & m_1(\neg F) & (m_1(F) \cup m_1(\neg F)) \\ m_2(F) & m_2(\neg F) & (m_2(F) \cup m_2(\neg F)) \end{pmatrix}$$

$m_{12}(\emptyset) = 0; \quad m_{12}(F) = 0.5936; \quad m_{12}(\neg F) = 0.0935;$
$m_{12}(F \cup \neg F) = 0.007;$

Then,

$k_{12} = m_{12}(F \cap \neg F) =$
$m_1(F)m_2(\neg F) + m_1(\neg F)m_2(F) = 0.3059;$

After we apply the value of k_{12} into eq. (7), we can obtain the result of Dempster's rule of combination. Then, we can get the degree of belief for "sleeping" situation and "fainting" situation using eq. (2).

$m_{DS}(F) = m_1(F_1) \oplus m_2(F_2) = \frac{1}{1-k_{12}} m_{12}(F) = 0.8552;$
$m_{DS}(\neg F) = \frac{1}{1-k_{12}} m_{12}(\neg F) = 0.1347;$
$m_{DS}(F \cup \neg F) = \frac{1}{1-k_{12}} m_{12}(F \cup \neg F) = 0.0101;$

$Bel(\{Sl\}) = m_{DS}(\{Sl\}) = m_{Sl}(\{Sl\}) = 0.7;$
$Pl(\{Sl\}) = m_{DS}(\{Sl\}) + m_{DS}(\{Sl, \neg Sl\})$
$= m_{Sl}(\{Sl\}) + m_{Sl}(\{Sl, \neg Sl\}) = 0.84;$
$Pl(\{Sl\}) - Bel(\{Sl\}) = m_{DS}(\{Sl, \neg Sl\}) = 0.14;$
$Bel(\{F\}) = m_{DS}(\{F\}) = 0.8552;$
$Pl(\{F\}) = m_{DS}(\{F\}) + m_{DS}(\{F, \neg F\}) = 0.8653;$
$Pl(\{F\}) - Bel(\{F\}) = m_{DS}(\{F, \neg F\}) = 0.0101;$

As a result, the value of Bel on "fainting" is greater than that on "sleeping" in DST approach. The value of (Pl - Bel) on "fainting" situation is also greater than that on "sleeping" situation. Hence we can infer that the situation of a patient is "fainting" situation.

4.4. Applying PCR5 rule of combination

For inferring "fainting" situation with PCR5 rule of combination, we first achieve the conjunctive consensus with the conflicting mass (k_{12}) as same as Dempster's rule of combination. After achieving (k_{12}), the partial conflicting mass $m_1(F)m_2(\neg F)$ is distributed to F and $\neg F$ proportionally with the masses $m_1(F)$ and $m_2(\neg F)$ assigned to F and $\neg F$ respectively. Also, the partial conflicting mass $m_2(F)m_1(\neg F)$ is distributed to F and $\neg F$ proportionally with the masses $m_2(F)$ and $m_1(\neg F)$ assigned to F and $\neg F$ respectively. Thus, we get two weighting factors of the redistribution for each corresponding set F and $\neg F$ respectively.

For example, we suppose that x_1 be the conflicting mass to be redistributed to F, and y_1 be the conflicting mass to be redistributed to $\neg F$ to calculate the first partial conflicting mass $m_1(F)m_2(\neg F)$.

$$\frac{x_1}{m_1(F)} = \frac{y_1}{m_2(\neg F)} = \frac{x_1+y_1}{(0.7)+(0.285)} = 0.2025;$$

Thus, $x_1 = 0.1418, \qquad y_1 = 0.0577;$

We also suppose that x_2 be the conflicting mass to be redistributed to F, and y_2 be the conflicting mass to be redistributed to $\neg F$ to calculate the second partial conflicting mass $m_2(F)m_1(\neg F)$.

$$\frac{x_2}{m_2(F)} = \frac{y_2}{m_1(\neg F)} = \frac{x_2+y_2}{(0.665)+(0.16)} = 0.129;$$

Thus, $x_2 = 0.0858, \qquad y_2 = 0.0206;$

According to eq. (8), we can obtain the result of PCR5 rule of combination. Then we can get the degree of belief for "fainting" situation using eq. (2).

$m_{PCR5}(F) = m_{12}(F) + x_1 + x_2 = 0.8212;$
$m_{PCR5}(\neg F) = m_{12}(\neg F) + y_1 + y_2 = 0.1718;$
$m_{PCR5}(F \cup \neg F) = m_{12}(F \cup \neg F) + 0 = 0.007;$

$Bel(\{F\}) = m_{PCR5}(\{F\}) = 0.8212;$
$Pl(\{F\}) = m_{PCR5}(\{F\}) + m_{PCR5}(\{F, \neg F\}) = 0.8282;$
$Pl(\{F\}) - Bel(\{F\}) = m_{PCR5}(\{F, \neg F\}) = 0.007;$

In DSmT approach, the value of Bel on "fainting" and the value of (Pl - Bel) on "fainting" are also greater than that on "sleeping" situation. Hence we can also infer that the situation of a patient is "fainting" situation.

4.5. Compare DSmT with DST

Based on the above results of two combination rules, we can infer the situation of a patient as "fainting" situation. However, we can also know that the conflicting mass of PCR5 rule ($m_{PCR5}(F \cup \neg F) = 0.007$) is less than that of Dempster's rule ($m_{DS}(F \cup \neg F) = 0.0101$) when we compare two rules of combination. This is because that Dempster's rule takes the total conflicting mass and redistributes it to all non-empty sets, even those not involved in the conflict. Table 3 shows examples of the degree of belief of patient's situation/acitivity using two rules of combination when different numbers of sensors are activated to recognize the "fainting" situation of a patient. In addition, Figure 3. shows a graph that represents uncertain levels ($m_{DS,PCR5}(F \cup \neg F)$) of two rules of combination based on the numbers of activated sensors.

Based on Table 3, the belief level of "fainting" situation is less than 50% when one or two sensors are activated. The belief level of that is sometimes over 50% when three

Table 3. Examples of the degrees of Belief based on numbers of activated sensor

Activated S	Bel(DS)	Pl(DS)	Bel(P5)	Pl(P5)
S	0.055	0.069	0.212	0.219
Bl	0.052	0.062	0.100	0.107
B,R	0.217	0.233	0.342	0.349
S,Bl	0.401	0.414	0.424	0.431
S,L,H	0.235	0.273	0.431	0.438
S,L,Bl	0.561	0.575	0.542	0.549
S,L,H,Bl	0.766	0.782	0.650	0.657
S,L,B,R	0.855	0.865	0.821	0.828
S,L,H,B,R	0.937	0.947	0.892	0.899
S,L,H,Bl,B,R	0.993	1.000	0.993	1.000

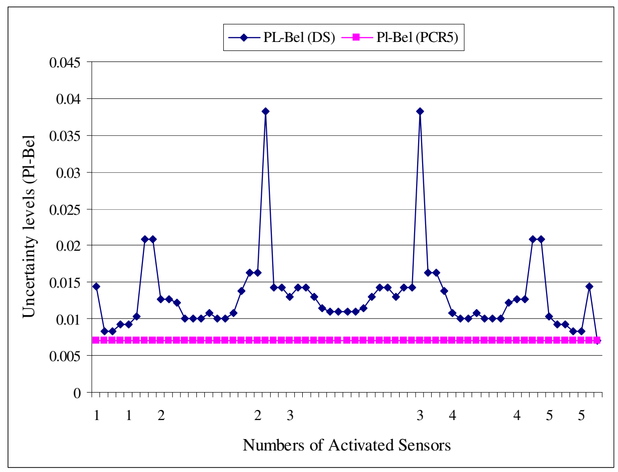

Figure 3. Uncertainty levels (Pl-Bel) based on the number of activated sensors

sensors are activated. The belief level of that is close to 1 when four or more sensors are activated. This result indicate that the "fainting" situation of a patient is recognized with a high degree of confidence when four or more sensors are activated. In addition, the uncertain levels (*Pl-Bel(DS)*) of DST are greater than those (*Pl-Bel(PCR5)*) of DSmT even if the values of *Bel(DS)* and *Pl(DS)* are greater than those of *Bel(PCR5)* and *Pl(PCR5)* in most of 50%+ cases as shown in Figure 3. Hence we can reduce the uncertain situation/activity of a patient whenever we apply PCR5 rule of combination into the home-based care scenario.

We also know that the belief level is affected by different weighting factors of each sensor. Thus, we apply different weighting factors into the applied scenario (No activation in sensor *Ls* and *Ts*) to show the variations of the degrees of belief as shown in Table 4. Based on Table 4, we correctly consider the designing of the weighting factors. The dis-

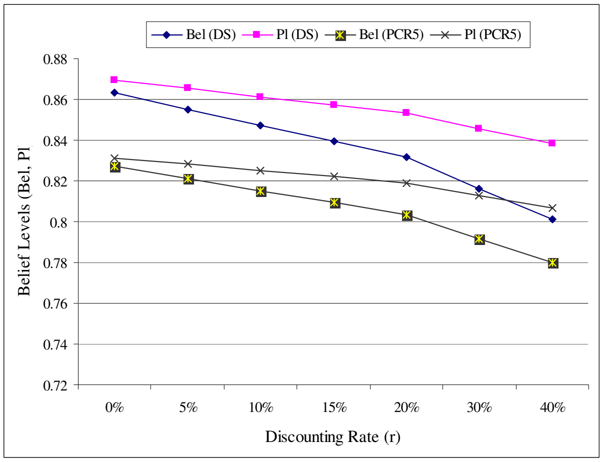

Figure 4. Belief on discounting rates (r)

counting rate r is also important to improve the belief level of a patient's situation/acticity. For instance, when we apply a different discounting rate r into a respiratory sensor *(R)*, the belief level is changed as shown in Figure 4. Increasing the discounting rate r of a respiratory sensor decreases the belief levels of "fainting" situation of a patient. Therefore, reducing the discounting rate r of each sensor is one method to increase the belief level of the situation of a patient.

5. Conclusion

In this paper, we utilize an evidential fusion approach that recognizes the situation(activity) of a patient in home-based care to reduce the different degrees of uncertainty in sensed data or in generated contexts. We also apply DSmT for fusion process instead of DST to mitigate the corrupted or conflicted contexts then to get higher belief levels in fusion process of contextual information. Finally, we analyze the improvement of DSmT fusion process by comparing Dempster's rule of combination and PCR5 rule of combination used in DST and DSmT respectively. We will continuously work to improve the quality of data by considering the weighting factor in context classifications. This is because that correctly designing the quality of data is one of important factor for reducing vague or conflicting information.

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Table 4. Belief on different weighting factors

S,L,H,Bl,B,R	Bel(DS)	Bel(P5)
(0.7,0.15,0.15,0.2,0.2,0.6)	0.706	0.649
(0.6,0.2,0.2,0.25,0.25,0.5)	0.734	0.689
(0.6,0.2,0.2,0.3,0.3,0.4)	0.855	0.821
(0.5,0.3,0.2,0.4,0.3,0.3)	0.804	0.772
(0.4,0.3,0.3,0.4,0.4,0.2)	0.864	0.833
(0.3,0.4,0.3,0.5,0.4,0.1)	0.895	0.847

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