A Static Evidential Network for Context Reasoning in Home-Based Care

Hyun Lee, *Member, IEEE*, Jae Sung Choi, and Ramez Elmasri, *Member, IEEE*

***Abstract*—In home-based care, reliable contextual information of remotely monitored patients should be generated by correctly recognizing the activities to prevent hazardous situations of the patient. It is difficult to achieve a higher confidence level of contextual information for several reasons. First, low-level data from multisensors have different degrees of uncertainty. Second, generated contexts can be conflicting, even though they are acquired by simultaneous operations. We propose the static evidential fusion process (SEFP) as a context-reasoning method. The context-reasoning method processes sensor data with an evidential form based on the Dezert–Smarandache theory (DSmT). The DSmT approach reduces ambiguous or conflicting contextual information in multisensor networks. Moreover, we compare SEFP based on DSmT with traditional fusion processes such as Bayesian networks and the Dempster–Shafer theory to understand the uncertainty analysis in decision making and to show the improvement of the DSmT approach compared to the others.**

***Index Terms*—Context reasoning, Dezert–Smarandache theory (DSmT), reliability, sensor data fusion process, static evidential networks (SENs).**

I. Introduction

A CONTEXTUAL analysis for situation assessment (SA) and metrics have been important topics in the information fusion (IF) literature for many years. An SA synthesizes different kinds of selected information using fusion processes, provides interfaces between the user and the automation, and focuses on data collection and management. Although an SA has been recognized in the IF and human factors literature, many issues in context-reasoning methods in some applications exist [1], [8], [25]. For instance, a pervasive healthcare monitoring system (PHMS) [13], which supports pervasive services to the patient using pervasive computing technologies (e.g., radio frequency identification (RFID) devices and multisensory) in home-based care can correctly analyze contextual information of the patient [2], [19], [20]. A PHMS enables continuous healthcare monitoring with the help of these embedded components and then provides methods for remote disease management in real time and independent safe living, as shown in Fig. 1. Reliable contextual information should be generated to correctly recognize the activities and then to identify hazardous situations of the patient by applying a context-reasoning method [18]. However, a higher confidence level in the generated contexts is difficult to produce due to the following reasons: 1) multisensors may not provide reliable information due to faults, operational tolerance levels, or corrupted data; 2) inaccurate sensor readings can produce misunderstandings that lead to incorrect services to the patient; 3) some sensor readings give information about context only at an abstract level, which can include uncertainty to some extent; and 4) contextual information of the patient is more ambiguous if data from multisensors are corrupted or conflicted. It is difficult to make a context-reasoning method for directly inferring the correct situation of the patient.

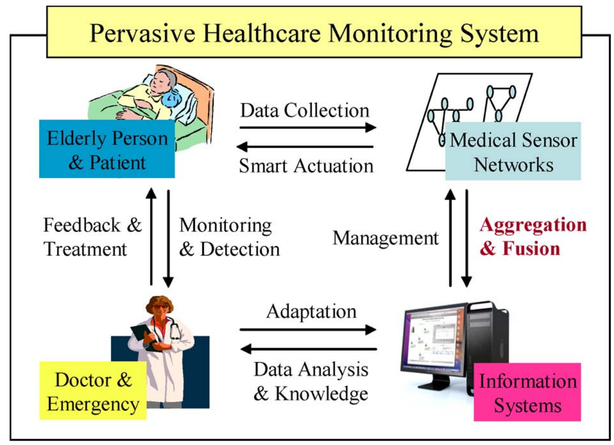


Fig. 1. Pervasive healthcare monitoring system.

To deal with these problems within a new application such as home-based care, first, we define a relation-dependency-based context classification and then construct a state-space context modeling based on the defined context classification [11]. Second, we make a static evidential fusion process (SEFP) as a context-reasoning method to obtain a higher confidence level of contextual information. In particular, we process sensor data with an evidential form based on the Dezert–Smarandache Theory (DSmT) [4]–[6]. DSmT reduces the uncertainty level and obtains a rational decision of contextual information using a proportional conflict redistribution 5 (PCR5) combination rule [27] and a generalized pignistic transformation (GPT) [7]. 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 [5]. Hence, the PCR5 rule is considered a combination rule in this paper. To take a rational decision, GPT generalizes the

Manuscript received June 3, 2009. Date of publication June 14, 2010; date of current version October 15, 2010. This paper was recommended by Associate Editor E. P. Blasch.

The authors are with the Department of Computer Science and Engineering, University of Texas at Arlington, Arlington, TX 76019 USA (e-mail: hlee@mavs.uta.edu; jschoi@uta.edu; emasir@uta.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TSMCA.2010.2046733

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 [28], [29]. 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. Finally, we compare SEFP based on DSmT with existing and contemporary methods such as Bayesian networks (BNs) [22], [24] and the Dempster–Shafer theory (DST) [10], [30] for performing an uncertainty analysis in decision making as to the ability to measure the probability, belief, or uncertainty levels in multisensor networks.

The rest of this paper is organized as follows. The basics of sensor data fusion methods are introduced in Section II. We define requirements for context reasoning in home-based care in Section III. SEFP is described as a context-reasoning method in Section IV. Section V performs a case study to infer the situation of the patient using the SEFP. We compare and then analyze the results of fusion processes in Section VI. We then conclude this paper in Section VII.

II. Basics of Sensor Data Fusion Methods

A. Bayesian and Probability Theories

To model probabilistic relationships among distinct interests in uncertain reasoning, BNs apply Bayes' theorem and satisfy Markov's condition [3]. BNs are directed acyclic graphs, where the nodes are random variables that represent various events, and the arcs between nodes represent causal relationships. The possibility of the particular configuration of BNs refers to an instantiation of the random variables with values from 2-D value vectors and is determined by its joint probability. When the precondition for inference is already available, we can compute a posterior probability distribution of a model. A learning operation in BNs may take place with either fully or partially observed variables. In any case, the objective of the learning is to find a single model that best explains the observed evidence. BNs do not necessarily require a transition from one state to another for computing the global or local state of the network. BNs compute a single higher level context as an abstraction of numerous primitive contexts. However, BNs cannot represent the ignorance [15], which manages the degree of uncertainty, caused by the lack of information.

B. DST

The DST (evidential theory) offers an alternative to probabilistic theory by providing schemes for encoding the epistemic uncertainty into the model of a system [26]. The DST is a generalization of traditional probability, which allows us to better quantify uncertainty. Shafer's model, denoted here by $M^0(\Theta)$, considers $\Theta = \{\theta_1, \ldots, \theta_n\}$ as a finite set of n exhaustive and exclusive elements that represent the possible states of the sensor. The set, denoted by Θ, is called *the frame of discernment* of the sensor in DST. For example, $\{1, 0\}$ is the frame of discernment for a sensor in which one (1) represents that the value of a sensor is more than the predefined threshold and zero (0) represents that the value is not more than the predefined threshold. The power set of Θ, denoted 2^Θ, is defined by the following rules 1, 2, and 3 given based on Θ and $M^0(\Theta)$.

1) $\emptyset, \theta_1, \ldots, \theta_n \in 2^\Theta$.
2) If $\theta_1, \theta_2 \in 2^\Theta$, then $\theta_1 \cup \theta_2$ belongs to 2^Θ.
3) No other elements belong to 2^Θ, except those obtained by rule 1 or 2.

Without loss of generality, the general set, denoted by G^Θ, on which will be defined the basic belief assignments is equal to 2^Θ if $M^0(\Theta)$ is adopted. In general, many factors that surround the sensor have an impact on the quality of the observation of the sensor. The evidential theory uses a number in the range [0, 1] to represent the degree of belief in the observation. The distribution of the unit of a belief over the frame (Θ) is called *evidence*. A mass function $m(.) : G^\Theta \rightarrow [0, 1]$ associated with a given source, e.g., s, of the evidence is defined to represent the distribution of a belief and to satisfy the following two conditions:

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

X is a subset of Θ, and $m_s(X)$ is the general basic belief assignment (GBBA) of X that the source s committed.

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

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

Based on (2), Bel shows the degree of a belief to which the evidence supports X, whereas Pl shows the degree of a belief to which the evidence fails to refute X. The DST is often employed to combine the evidence gathered from two or more independent sources to minimize the effect of imprecision. As a generalized probabilistic approach, the DST, which considers the upper and lower bounds on probability, has distinct features compared to Bayesian methods. The DST represents the ignorance caused by the lack of information and aggregates the belief when new evidences are accumulated [10]. This feature is useful for managing the degree of uncertainty.

C. DSmT

The basic idea of DSmT is to consider all elements of Θ as not precisely defined and separated so that no refinement of Θ into a new finer set Θ^{ref} of disjoint hypotheses is possible in general, unless a number of integrity constraints are known, and in such a case, they will be included in the DSm model of the frame. Shafer's model [26] assumes Θ to be truly exclusive and appears only as a special case of the DSm hybrid model in DSmT. The hyperpower set, denoted by D^Θ, is defined by rules 1, 2, and 3, without additional assumption on Θ but the exhaustivity of its elements in DSmT.

1) $\emptyset, \theta_1, \ldots, \theta_n \in D^\Theta$.
2) If $\theta_1, \theta_2 \in D^\Theta$, then $\theta_1 \cap \theta_2$ and $\theta_1 \cup \theta_2$ belong to D^Θ.
3) No other elements belong to D^Θ, except those obtained by rule 1 or 2.

When $M^0(\Theta)$ holds, D^Θ reduces to 2^Θ. Without loss of generality, G^Θ is equal to D^Θ if the DSm model is used, depending on the nature of the problem.

D. Combination Rules (Dempster's and PCR5)

Both combination rules (Dempster's and PCR5) are defined based on the conjunctive consensus operator for two sources cases by

$$m_{12}(X) = \sum_{\substack{X_1, X_2 \in G^\Theta \\ X_1 \cap X_2 = X}} m_1(X_1) m_2(X_2). \tag{3}$$

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

$$k_{12} = \sum_{\substack{X_1, X_2 \in G^\Theta \\ X_1 \cap X_2 = \emptyset}} m_1(X_1) m_2(X_2) = \sum_{\substack{X_1, X_2 \in G^\Theta \\ X_1 \cap X_2 = \emptyset}} m(X_1 \cap X_2). \tag{4}$$

Based on (3) and (4), the total conflicting mass is the sum of partial conflicting masses. If k_{12} is close to 1, the two sources are almost in total conflict, whereas if k_{12} is close to 0, the two sources are not in conflict.

Within the DST framework, Dempster's combination rule of $m_1(.)$ and $m_2(.)$ is obtained based on $M^0(\Theta)$ 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

$$m_{DS}(X) = \frac{1}{1 - k_{12}} m_{12}(X), \qquad (k_{12} \neq 1) \tag{5}$$

where $m_{12}(X)$ and k_{12} are defined by (3) and (4). Dempster's rule can directly be extended for the combination of N independent and equally reliable sources of evidence.

However, Dempster's combination rule has limitations and weaknesses. The results of the combination have low confidence when a conflict becomes important between sources [4], [6], [16]. For instance, consider $\Theta = \{\theta_1, \theta_2\}$ and the basic belief masses that are represented by the following mass matrix:

$$\mathbf{M} = \begin{pmatrix} m_1(\theta_1) = 1 & m_1(\theta_2) = 0 & m_1(\theta_1 \cup \theta_2) = 0 \\ m_2(\theta_1) = 0 & m_2(\theta_2) = 1 & m_2(\theta_1 \cup \theta_2) = 0 \end{pmatrix}.$$

In this case, Dempster's combination rule cannot be applied, because the conflicting mass of two independent evidences is equal to 1 ($k_{12} = 1$). Then, one formally gets $m_{12}(\theta_1) = 0/0$ and $m_{12}(\theta_2) = 0/0$. However, if one adopts $M^0(\Theta)$ and applies the PCR5 rule as a combination rule, one formally gets $m_{12}(\theta_1) = 0.5$ and $m_{12}(\theta_2) = 0.5$. Hence, we use the PCR5 combination rule, which overcomes drawbacks of Dempster's combination rule.

Within the DSmT framework, the PCR5 combination rule redistributes the partial conflicting mass only to the elements involved in that partial conflict. For this approach, first, the PCR5 rule calculates the conjunctive rule of the belief masses of sources. Second, the PCR5 rule calculates the total or partial conflicting masses. Last, the PCR5 rule proportionally redistributes the conflicting masses to nonempty sets involved in the model according to all integrity constraints.

The PCR5 combination rule is defined for two sources [6]: $m_{\mathrm{PCR5}}(\emptyset) = 0$ and $\forall\,(X \neq \emptyset) \in G^\Theta$. We have

$$m_{\mathrm{PCR5}}(X) = m_{12}(X) + \sum_{\substack{Y \in G^\Theta \setminus \{X\} \\ X \cap Y = \emptyset}} \left[\frac{m_1(X)^2 m_2(Y)}{m_1(X) + m_2(Y)} + \frac{m_2(X)^2 m_1(Y)}{m_2(X) + m_1(Y)} \right] \tag{6}$$

where m_{12} and all denominators such as $m_1(X) + m_2(Y)$ and $m_2(X) + m_1(Y)$ differ from zero (0). If a denominator is zero, that fraction is discarded. All sets in formulas are in canonical forms. For example, the canonical form of $X = (A \cap B) \cap (A \cup B \cup C)$ is $A \cap B$.

E. Pignistic Transformations: CPT and GPT

When a decision must be taken, the expected utility theory, which requires a CPT from a basic belief assignment $m(.)$ to a probability function $P\{.\}$, is defined in [7] as follows:

$$P\{A\} = \sum_{X \in 2^\Theta} \frac{|X \cap A|}{|X|} m(X) \tag{7}$$

where $|A|$ denotes the number of worlds in the set A (with convention $|0|/|0| = 1$, to define $P\{0\}$). $P\{A\}$ corresponds to $BetP(A)$ in Smets' notation [28]. Decisions are achieved by computing the expected utilities, and the maximum of the pignistic probability is used as a decision criterion.

Within the DSmT framework, it is necessary to generalize the CPT to take a rational decision. This GPT is defined by [7]: $\forall\,(A) \in D^\Theta$. We have

$$P\{A\} = \sum_{X \in D^\Theta} \frac{C_M(X \cap A)}{C_M(X)} m(X) \tag{8}$$

where $C_M(X)$ denotes the DSm cardinal of a proposition X for the DSm model M of the problem under consideration.

In this case, if we adopt $M^0(\Theta)$, (8) reduces to (7) when D^Θ reduces to 2^Θ. For instance, we get a basic belief assignment with nonnull masses only on θ_1, θ_2 and $\theta_1 \cup \theta_2$. After applying the GPT, we get

$$\begin{aligned} P\{\emptyset\} &= 0 \qquad P\{\theta_1 \cap \theta_2\} = 0 \\ P\{\theta_1\} &= m(\theta_1) + \frac{1}{2} m(\theta_1 \cup \theta_2) \\ P\{\theta_2\} &= m(\theta_2) + \frac{1}{2} m(\theta_1 \cup \theta_2) \\ P\{\theta_1 \cup \theta_2\} &= m(\theta_1) + m(\theta_2) + m(\theta_1 \cup \theta_2) = 1. \end{aligned}$$

F. Disjunctive Rule for the TBF

The temporal belief filter (TBF) [21], which reflects that only one hypothesis concerning activity is true at each time point, ensures a temporal consistency with an exclusivity. Within a

TBF, the disjunctive rule of combination $(m_{\cup}(.))$ is used for computing the prediction from the previous mass distributions and the model of evolution. $m_{\cup}(.)$ is defined for two sources [4]: 1) $m_{\cup}(\emptyset) = 0$ and 2) $\forall (C) \subset \Theta$. We have

$$m_{\cup}(C) = \sum_{\substack{i,j \\ C = X_i \cup Y_j}} m_1(X_i) m_2(Y_j), \qquad C \neq \emptyset \tag{9}$$

where the core of the belief function given by $m_{\cup}(C)$ is equal to the union of the cores $Bel(X)$ and $Bel(Y)$.

III. Requirements for Context Reasoning

A. Characteristics of Sensors

Multisensors such as medical body sensors, RFID devices, environmental sensors and actuators, location sensors, and time stamps are utilized in a PHMS [13]. These sensors are operated by predefined rules or learning processes of the expert systems. They often have thresholds to represent the emergency status of the patient or to operate actuators. Each sensor can be represented by an evidential form such as 1 (active) and 0 (inactive) based on the threshold. Whenever the state of a certain context associated with a sensor is changed, the value of a sensor can change from 0 to 1 or from 1 to 0. For instance, a medical body sensor activates the emergency signal if the sensor value is more than the predefined threshold. An environmental sensor operates the actuator based on the fuzzy systems. A location-detecting sensor operates if a patient is within the range of the detection area. Thus, we can simply express the status of each sensor as a frame: $\Theta = \{Threshold_{over}, Threshold_{not-over}\} = \{1, 0\}$.

Sensor data are inherently unreliable or uncertain due to technical factors and environmental noise. Different sensors may have various discounting factors [error rates (r)]. Hence, we can express the degree of reliability, which is related in an inverse way to the discounting factor. The smaller reliability R corresponds to a larger discounting factor D, i.e.,

$$R = 1 - D(r). \tag{10}$$

To infer the activity based on evidential theory, reliability discounting methods that transform beliefs of each source are used to reflect the sensor's credibility, in terms of discount factor [error rate (r)] $(0 \leq r \leq 1)$. The discount mass function is defined as

$$m^r(X) = \begin{cases} (1-r)m(X), & X \subset \Theta \\ r + (1-r)m(\Theta), & X = \Theta \end{cases} \tag{11}$$

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

B. Context Classification

Contextual information of the patient should be presented by a generalized form, and the quality of a given piece of contextual information should be considered by the applied context classification. It is difficult to make a generalized context classification, because the number of ways to describe an event or an object is unlimited, and there are no standards or guidelines regarding the granularity of contextual information. Hence, we apply the relation-dependency-based context classification, which is proposed in [11]. The dependency is a special type of relationship that exists not between entities and attributes but between associations themselves [9]. Without knowledge of such dependencies, inappropriate decisions may be made by the context-aware applications, which can lead to wrong operations to the patient. Therefore, we consider the relation-dependency approach based on spatial–temporal criteria, as shown in Fig. 2. In this approach, contexts are represented by three relation dependencies: 1) discrete facts; 2) continuous facts; and 3) patient's interaction. These relation-dependency components consist of context state $(S(t))$, sensor's static threshold $(T(t))$, location of the patient $(R(t))$, primary context (P), secondary context (S), and preference $(Pref)$.

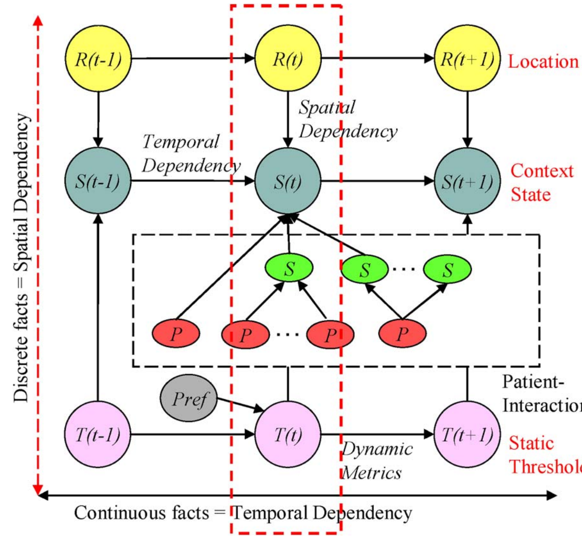


Fig. 2. Relation-dependency approach as the applied context classification.

1) Discrete Facts: The context can be expressed by three types of discrete facts: 1) discrete value; 2) enumerative set; and 3) state context. The discrete value of a context has no dependency. It can directly lead to contextual information in some cases. In general, the values of context are defined in a list or a set of discrete values. The enumerative set is constructed with this finite set of attributes that are chosen at any given time and location, although the total size of the set may theoretically be infinite. The state context, which consists of a form of an enumerative set, has two opposite values and can toggle between them. It is useful to make a binary evidential fusion process. For instance, a state context, which is composed of the enumerative set, can recognize the particular contextual information of the patient: 1) *Emergency* or 2) *No Emergency*.

2) Continuous Facts: The context can be expressed by two types of continuous facts: 1) static threshold and 2) dynamic metrics. The static threshold of a context is defined by predefined rules, although the value of a context continuously changes. Upper bounds, lower bounds, and comparative criteria are involved in this category. The dynamic metrics, which combine preference values into the static threshold, are

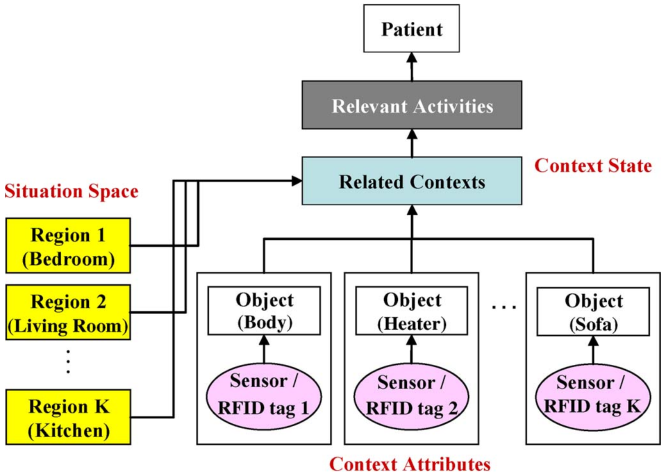


Fig. 3. Hierarchical interrelationship among multisensors, related contexts, and relevant activities based on the state-space modeling.

used to autonomously estimate or infer the future contextual information.

3) Patient-Interaction Events: Two types of context, primary context P and secondary context S, are derived from multisensor or information sources. P directly maintains a one-to-one interaction event, which has a discrete value. S maintains two different interactions: 1) many-to-one interactions and 2) one-to-many interactions. More than one P (e.g., humidity, temperature, and lighting level) may be needed to generate S (e.g., patient's feeling) in many-to-one interaction events. In addition, one P (e.g., the value of a respiratory rate sensor) may be needed to generate S (e.g., sleeping situation) in one-to-many interaction events.

C. State-Space-Based Context Modeling

A state-space-based context modeling with an evidential form is defined in [11] to represent the situation of the patient using context concepts, which is similarly used in [17]. Static weighting factors of the selected data within the given time and location are applied to represent the quality of data. This context modeling consists of a hierarchical interrelationship among multisensors, related contexts, and relevant activities within a selected region, as shown in Fig. 3. Each context concept is defined as follows.

1) Context Attribute: A *context attribute*, denoted by α_i, is defined as any type of data that are utilized in inferring situations. A context attribute is often associated with sensors, virtual or physical, where the value of a sensor reading denotes the value of a context attribute at a given time t, denoted by α_i^t. For example, the pressure sensor attached on the sofa or the temperature sensor attached on the body of the patient is an example of a context attribute. This sensor cannot directly identify situations on its own, but it can estimate the situation by combining its values as context attributes.

2) Context State: A *context state*, denoted by a vector S_i, describes the current state of the applied application in relation to a chosen context. It is a collection of K context attribute values, which are used to represent a specific state of the system at the given time t. A context state is denoted as $S_i^t = (\alpha_1^t, \alpha_2^t, \ldots, \alpha_K^t)$, where each value α_i^t corresponds to the value of an attribute α_i at the given time t. Whenever contextual information is recognized by certain selected sensors, which can be used to make a context attribute, a context state changes its current state, depending on the aggregation of these context attributes. For instance, a context state that consists of context attributes such as the body temperature sensor, the blood pressure sensor, and the respiratory rate sensor can indicate an emergency situation of the patient, depending on the values of the sensors.

3) Situation Spaces: A *situation space*, denoted by a vector space $R_i = (\alpha_1^R, \alpha_2^R, \ldots, \alpha_K^R)$, describes a collection of regions corresponding to predefined situations and that consists of K 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., $\alpha_i^R = V \setminus P(V)$. The particular contextual information can be performed or associated with a certain selected region. For example, a sleeping activity of the patient, which is predefined in the expert system, can be associated with a selected region such as a bedroom or a living room.

4) Quality of Data: Given a context attribute i, a *quality of data* ψ_i associates weights $\omega_1, \omega_2, \ldots, \omega_K$ with combined attributes of values $\alpha_1^t + \alpha_1^R, \alpha_2^t + \alpha_2^R, \ldots, \alpha_K^t + \alpha_K^R$ of i, respectively, where $\sum_{j=1}^K \omega_j = 1$. The weight $\omega_j \in (0, 1]$ represents the relative importance of a context attribute α_j compared to other context attributes in the given time t and region R. For instance, a higher respiratory rate may be a strong indication of the fainting situation of a patient, whereas other context attributes such as a blood pressure sensor and a body temperature sensor may not be very important to estimate that specific situation compared to the respiratory rate sensor. In addition, a context attribute (α_i^t) within a context state $(S_i^t = (\alpha_1^t, \alpha_2^t, \ldots, \alpha_K^t))$ has various individual weights for α_i^t per different time intervals in the same situation space (α_i^R). For example, a respiratory rate (50 Hz) at the current time is a stronger indication of the fainting situation of a patient compared with a respiratory rate (21 Hz) at a previous time. However, the same context attribute can also have a different degree of importance when considered in different contexts. Thus, we only consider the quality of data with the predefined context attributes, a selected region, and relevant activities, i.e., sleeping or fainting in this paper.

IV. SEFP

Context reasoning is performed based on static evidential networks (SENs) to reduce the uncertainty of a patient's situation and to help in decision making. Using evidential fusion processes such as the frame of discernment, the multivalued mapping, the combination rule, and the belief filter, we can apply context reasoning based on evidential fusion networks.

A. Evidential Operations With SENs

To infer the activity of the patient along SENs, first, the evidential form, which is either active (1) or inactive (0), can represent all possible values and their combination values of the sensors. Table I shows an example of evidential forms such

TABLE I
EXAMPLES OF THE FRAMES OF DISCERNMENT Θ

Name	Type	Frame of discernment
Sensor 1	Sensor	$\{Threshold_{over}, \neg Threshold_{over}\}$
Attribute 1	Attribute	$\{Active, Inactive\}$
State 1	State	$\{State_{-On}, State_{-Off}\}$

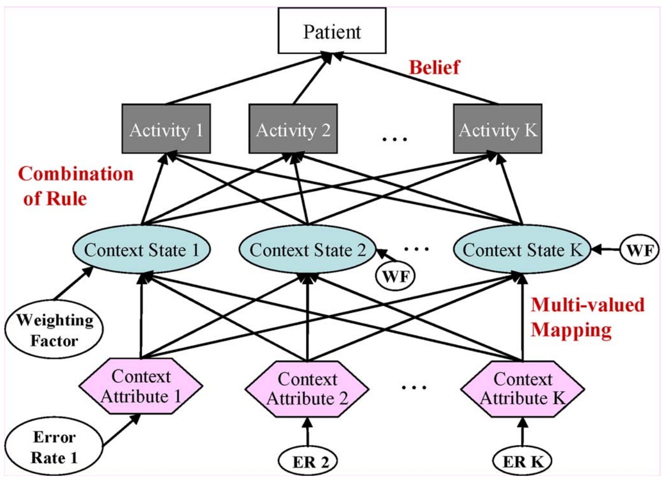


Fig. 4. Static evidential network based on state-space context modeling.

as *the frames of discernment* (Θ). This evidential form can be a component of the SENs.

Based on the proposed state-space context modeling, the SEN is constructed as shown in Fig. 4. Within a SEN, context reasoning is performed to make a higher confidence level of the patient's situation. In this case, a context attribute consists of binary values of the multisensors. The binary values are determined by the predefined threshold values controlled by the expert system.

Second, reliability discounting methods (mass functions), which is defined as in (11), transform beliefs of individual sources to reflect the *credibility* of the sensor. Within a SEN, a discounting factor [error rate (r)] that depends on the technical limitations of the sensors or environmental noise is applied to each context attribute.

Third, *multivalued mapping* is applied to reflect the relationship between two frames of discernment (Θ_A, Θ_B), which represent the evidence to the same problem with different views. A multivalued 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 multivalued mapping, a translation can be utilized to determine the impact of evidence that originally appears 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; then, the translated mass function over the compatibly related Θ_B is defined as

$$m'(B_j) = \sum_{\Gamma(e_i)=B_j} m(e_i) \tag{12}$$

where $e_i \in \Theta_A$, $B_j \subseteq \Theta_B$, and $\Gamma : \Theta_A \rightarrow 2^{\Theta_B}$ is a multivalued mapping.

Within a SEN, a multivalued mapping is applied to the context attributes to represent the relationships between sensors and associated objects by translating mass functions. In addition, this mapping is applied to the related context state,

TABLE II
EXAMPLES OF MULTIVALUED MAPPING

Relationship	Multi-valued mapping
Sensor (S)$\rightarrow$Object (O)	$\{S\} \rightarrow \{O\}$; $\{\neg S\} \rightarrow \{\neg O\}$; $\{(S, \neg S)\} \rightarrow \{(O, \neg O)\}$;
Object (O) $\rightarrow$ State (O_1, O_2)	$\{O\} \rightarrow \{(O_1, O_2)\}$; $\{\neg O\} \rightarrow \{\neg(O_1, O_2)\}$; $\{(O, \neg O)\} \rightarrow \{(O_1, O_2), \neg(O_1, O_2)\}$;
State $(O_1, O_2)\rightarrow$ Activity (A_1)	$\{(O_1, O_2)\} \rightarrow \{A_1\}$; $\{\neg(O_1, O_2)\} \rightarrow \{\neg A_1\}$; $\{(O_1, O_2), \neg(O_1, O_2)\} \rightarrow \{(A_1), \neg(A_1)\}$;

which consists of context attributes having an active (1) value and an inactive (0) value, to represent the relationships among context attributes. In this case, each context state has different static weighting factors. These weighting factors help infer an activity using a multivalued mapping among context states. We assume that the weighting factors of context state (S_1) and (S_2) are 0.5 and 0.5, respectively. Table II shows an example of a multivalued mapping.

Fourth, the belief distributions on the same frame can be combined by several independent sources of the evidence to achieve the conjunctive consensus with the conflict mass. Within the DST framework, the Dempster's combination rule (5) is used. However, within the DSmT framework, the PCR5 rule (6) is currently used as a combination rule. Regardless of whether the conflicting mass is bigger or smaller, the PCR5 rule mathematically does a better redistribution of the conflicting mass than other rules, because the PCR5 rule goes backward on the tracks of the conjunctive rule. Within a SEN, the PCR5 rule is applied to context states to get a consensus for recognizing the activity of the patient.

Finally, a range of probabilities (the lower and upper bounds on probability) are calculated to represent the degree of belief using (2), and then, the uncertainty levels (ignorance) in the evidential framework is measured by using belief functions such as Bel and Pl after applying two combination rules.

Uncertainty levels$(=$ ignorance). We have

$$\text{Uncertainty Levels (I)} = Pl - Bel. \tag{13}$$

To make a decision, the expected utility and the maximum of the pignistic probability (8) is utilized as a decision criterion. Within a SEN, the situation of the patient is inferred by calculating the belief and uncertainty levels with a decision rule such as the GPT.

Therefore, the procedures of the SEFP, which is a context-reasoning method, 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 using (10) and (11) to get sensor credibility.
3) Translate a multivalued mapping representing relationships between sensors and associated objects to make a context attribute using (12).
4) Aggregate context attributes and then translate using (12) 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 using (3)–(6).
7) Calculate the belief levels, uncertainty levels, and the maximum of pignistic probability of each activity and then make a decision using (1), (2), (7), (8), and (13).

B. TBF for Temporal Consistency

A TBF can be used to ensure temporal consistency with an exclusivity between two consecutive time stamps when only one hypothesis concerning activity is true at each time. The TBF assumes that the GBBA at the current time (t) is close to the GBBA at the previous time $(t-1)$. Based on this assumption, a model of evolution predicts the current GBBA taking the GBBA at $(t-1)$ into account. The TBF process works at each time (t) and consists of four steps: 1) prediction; 2) fusion; 3) detection of conflict; and 4) model change, if required [21].

For instance, if the activity of the patient was "fainting" (F) at time $(t-1)$, then it would be partially "fainting" (F) at time (t). This approach is an implication rule for F, which can be weighted by a confidence value of $m_F\{.\} \in [0,1]$. In this case, the vector notation of a GBBA defined on (Θ) is used

$$m^\Theta = [\, m^\Theta(\emptyset) \quad m^\Theta(\neg F) \quad m^\Theta(F) \quad m^\Theta(\neg F \cup F) \,].$$

A model of evolution can be interpreted as a GBBA defined as

$$m_F^\Theta = [0 \quad 1 - Pl_F \quad Bel_F \quad Pl_F - Bel_F]^T. \tag{14}$$

Depending on the current model M with only two focal sets, the disjunctive rule of combination is used for computing the *prediction* from the previous GBBA at $(t-1)$ and the model of evolution using (9)

$$\hat{m}^\Theta_{t,M} = m^\Theta_{t-1} \quad (M_\cup) \quad m^\Theta_M \tag{15}$$

where m^Θ_{t-1} is the previous GBBA, and m^Θ_M is the model of evolution. In addition, the prediction for the fainting F of the patient at t is defined as

$$\hat{\mathbf{m}}^\Theta_{t,F} = \begin{bmatrix} 0 \\ 1 - Pl_F \times m^\Theta_{t-1}(\neg F) \\ Bel_F \times m^\Theta_{t-1}(F) \\ 1 - \left(1 - Pl_F \times m^\Theta_{t-1}(\neg F) + Bel_F \times m^\Theta_{t-1}(F)\right) \end{bmatrix} \tag{16}$$

and when $m_F = 1$ or 0, the prediction reflects a total confidence or a total ignorance with the current state, respectively.

Prediction $\hat{m}^\Theta_{t,M}$ and measurement m^Θ_t represent two distinct pieces of information. The *fusion* of the two distinct pieces of information leads to a new GBBA whose conflict value (C_F), which is similar to k_{12} of (4), is relevant for model change requirement. *Detection of conflict* is required to analyze whether the current model is valid. If the C_F is not greater than a predefined threshold, the model is kept as valid. However, if the C_F exceeds the predefined threshold, the model is changed. After a *model change*, the new model is repeatedly applied to the model evolution.

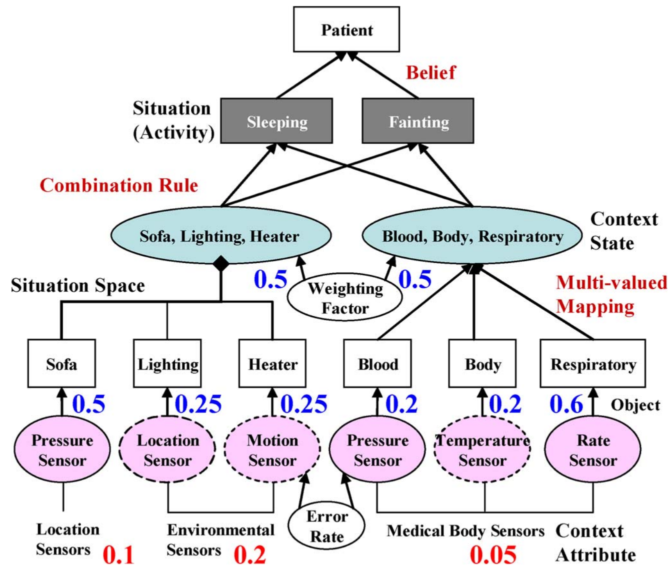


Fig. 5. Example of patient's two possible context reasoning based on the SEN.

V. Case Study

A. Applied Scenario

Many ambiguous situations of the patient can happen in home-based care. Suppose that two possibilities (i.e., sleeping or fainting) of the patient can happen on the sofa when the environmental sensors (i.e., the lighting sensor and the heating sensor of the living room) are turned on and the location sensor (i.e., the pressure sensor attached on the sofa) becomes active. To continuously check the status of the patient, medical body sensors (i.e., the blood pressure sensor, the body temperature sensor, and the respiratory rate sensor) are operated by the expert system. 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. 5. 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 each sensor are fixed. In addition, we assume that a static weighting factor of the pressure sensor, the location sensor, the motion sensor, the blood pressure sensor, the body temperature sensor, and the respiratory rate sensor are 0.5, 0.25, 0.25, 0.2, 0.2, and 0.6, respectively. Three sensors—the location sensor, the motion sensor, and the body temperature sensor—are not activated in Fig. 5.

B. Situation Inference

We can infer the situation of the patient using the proposed evidential fusion method. Within a scenario, an evidence of the sensor operation may deduce objects in detail or be summed up to a context state by adapting a different weighting factor. That evidence is then translated into the relevant activity recognition by applying a multivalued mapping. On an activity recognition step, several belief distributions can be combined by different rules (Dempster's & PCR5) of combination. Then, a decision is made by using the degree of belief, uncertainty, maximum of pignistic probability, and TBF. Based on the simplified scenario, context reasoning is performed by some steps of evidential operations as described in [12].

First, we represent abbreviations for the pressure sensor Ps, the location sensor Ls, the motion sensor Ms, the blood pressure sensor Bps, the body temperature sensor Bts, and the respiratory rate sensor Rs in Fig. 5. We then represent a piece of evidence on each sensor as a mass function. We have

$$\begin{aligned} &m_{Ps}(\{Ps\}) = 1 \qquad m_{Ls}(\{\neg Ls\}) = 1 \\ &m_{Ms}(\{\neg Ms\}) = 1 \qquad m_{Bps}(\{Bps\}) = 1 \\ &m_{Bts}(\{\neg Bts\}) = 1 \qquad m_{Rs}(\{Rs\}) = 1. \end{aligned}$$

Second, we apply an error rate r to each sensor using (10) and (11) to obtain each sensor credibility. Within our scenario, we assume that the location sensor Ps has a 10% error rate, the environmental sensors (Ls and Ms) have a 20% error rate, and the medical body sensors (Bps, Bts, and Rs) 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 using (12). We utilize abbreviations for the sofa S, the lighting L, the heater H, the blood pressure check device Bp, the body temperature check device Bt, and the respiratory rate check device R. We then aggregate context attributes and translate them into two related context states using (12). A mass function on S, L, and H are translated onto the context state 1 ($CS1$), and a mass function on Bp, Bt, and R is translated onto the context state 2 ($CS2$). Both $CS1$ and $CS2$ are used for determining the relevant activities of the patient, i.e.,

$$\begin{aligned} m1_{CS1}(\{CS1\}) &= m_S(\{S\}) = m^r_{Ps}(\{Ps\}) = 0.90 \\ m1_{CS1}(\{CS1, \neg CS1\}) &= m_S(\{S, \neg S\}) \\ &= m^r_{Ps}(\{Ps, \neg Ps\}) = 0.10 \\ m2_{CS1}(\{\neg CS1\}) &= m_L(\{\neg L\}) = m^r_{Ls}(\{\neg Ls\}) = 0.80 \\ m2_{CS1}(\{CS1, \neg CS1\}) &= m_L(\{L, \neg L\}) \\ &= m^r_{Ls}(\{Ls, \neg Ls\}) = 0.20 \\ m3_{CS1}(\{\neg CS1\}) &= m_H(\{\neg H\}) = m^r_{Ms}(\{\neg Ms\}) = 0.80 \\ m3_{CS1}(\{CS1, \neg CS1\}) &= m_H(\{H, \neg H\}) \\ &= m^r_{Ms}(\{Ms, \neg Ms\}) = 0.20 \\ m1_{CS2}(\{CS2\}) &= m_{Bp}(\{Bp\}) = m^r_{Bps}(\{Bps\}) = 0.95 \\ m1_{CS2}(\{CS2, \neg CS2\}) &= m_S(\{Bp, \neg Bp\}) \\ &= m^r_{Bps}(\{Bps, \neg Bps\}) = 0.05 \\ m2_{CS2}(\{\neg CS2\}) &= m_{Bt}(\{\neg Bt\}) = m^r_{Bts}(\{\neg Bts\}) \\ &= 0.95 \\ m2_{CS2}(\{CS2, \neg CS2\}) &= m_{Bt}(\{Bt, \neg Bt\}) \\ &= m^r_{Bts}(\{Bts, \neg Bts\}) = 0.05 \\ m3_{CS2}(\{CS2\}) &= m_R(\{R\}) = m^r_{Rs}(\{Rs\}) = 0.95 \\ m3_{CS2}(\{CS2, \neg CS2\}) &= m_R(\{R, \neg R\}) \\ &= m^r_{Rs}(\{Rs, \neg Rs\}) = 0.05. \end{aligned}$$

Third, we sum up a context state by adapting a different static weighting factor to each context attribute involved in the context state. We assume that the weighting factor of $CS1$ consists of S (50%), L (25%), and H (25%), and the weighting factor of $CS2$ consists of Bp (20%), Bt (20%), and R (60%). We have

$$\begin{aligned} m_{CS1}(\{CS1\}) &= (0.5)(m1_{CS1}) = 0.45 \\ m_{CS1}(\{\neg CS1\}) &= (0.25)(m2_{CS1} + m3_{CS1}) = 0.40 \\ m_{CS1}(\{CS1, \neg CS1\}) &= (0.5)(m1_{CS1}) \\ &\quad + (0.25)(m2_{CS1} + m3_{CS1}) \\ &= 0.15 \\ m_{CS2}(\{CS2\}) &= (0.2)(m1_{CS2}) + (0.6)(m3_{CS2}) = 0.76 \\ m_{CS2}(\{\neg CS2\}) &= (0.2)(m2_{CS2}) = 0.19 \\ m_{CS2}(\{CS2, \neg CS2\}) &= (0.2)(m1_{CS2} + m2_{CS2}) \\ &\quad + (0.6)(m3_{CS2}) = 0.05. \end{aligned}$$

We assume that both $CS1$ and $CS2$ can be used for inferring the sleeping (Sl) and fainting (F) situations of the patient. In this paper, we calculate two mass functions $m1_F$ and $m2_F$ to identify the F situation of the patient, i.e.,

$$\begin{aligned} m1_F(\{F\}) &= m_{CS1}(\{CS1\}) = 0.45 \\ m1_F(\{\neg F\}) &= m_{CS1}(\{\neg CS1\}) = 0.40 \\ m1_F(\{F, \neg F\}) &= m_{CS1}(\{CS1, \neg CS1\}) = 0.15 \\ m2_F(\{F\}) &= m_{CS2}(\{CS2\}) = 0.76 \\ m2_F(\{\neg F\}) &= m_{CS2}(\{\neg CS2\}) = 0.19 \\ m2_F(\{F, \neg F\}) &= m_{CS2}(\{CS2, \neg CS2\}) = 0.05. \end{aligned}$$

Fourth, we apply (3)–(5) to $m1_F$ and $m2_F$ to achieve the conjunctive consensus by combining two sources with the conflicting mass (k_{12}). We then redistribute the partial conflicting mass using (6) as follows:

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

$$\begin{aligned} m_{12}(\emptyset) &= 0 \qquad m_{12}(F) = 0.4785 \\ m_{12}(\neg F) &= 0.1245 \qquad m_{12}(F \cup \neg F) = 0.0075 \\ k_{12} &= m_{12}(F \cap \neg F) \\ &= m_1(F)m_2(\neg F) + m_1(\neg F)m_2(F) \\ &= 0.3895 \\ m_{DS}(F) &= m_1 \oplus m_2(F) = \frac{1}{1 - k_{12}} m_{12}(F) \\ &= 0.7838 \\ m_{DS}(\neg F) &= \frac{1}{1 - k_{12}} m_{12}(\neg F) = 0.2039 \\ m_{DS}(F \cup \neg F) &= \frac{1}{1 - k_{12}} m_{12}(F \cup \neg F) = 0.0123. \end{aligned}$$

After achieving the value of 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. We suppose that x_1 and y_1 is the conflicting mass to be redistributed to F and $\neg F$, respectively, to calculate the first partial conflicting mass $m_1(F)m_2(\neg F)$ as follows:

$$\frac{x_1}{m_1(F)} = \frac{y_1}{m_2(\neg F)} = \frac{x_1 + y_1}{(0.45) + (0.19)} = 0.1336.$$

Thus, $x_1 = 0.0601$, $y_1 = 0.0254$.

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

$$\frac{x_2}{m_2(F)} = \frac{y_2}{m_1(\neg F)} = \frac{x_2 + y_2}{(0.76) + (0.40)} = 0.2621.$$

Thus, $x_2 = 0.1992$, $y_2 = 0.1048$.

We can obtain two results of the redistribution for each corresponding set F and $\neg F$, respectively. We then obtain the result of the PCR5 rule based on the (6) as follows:

$$\begin{aligned} m_{\mathrm{PCR5}}(F) &= m_{12}(F) + x_1 + x_2 = 0.7378 \\ m_{\mathrm{PCR5}}(\neg F) &= m_{12}(\neg F) + y_1 + y_2 = 0.2547 \\ m_{\mathrm{PCR5}}(F \cup \neg F) &= m_{12}(F \cup \neg F) + 0 = 0.0075. \end{aligned}$$

Finally, we calculate the belief and uncertainty level of the F situation with two combination rules using (1), (2), and (13). We then calculate the maximum of pignistic probability with a decision rule using (7) and (8), i.e.,

$$\begin{aligned} Bel(\{F\}) &= m_{DS}(\{F\}) = 0.7838 \\ Pl(\{F\}) &= m_{DS}(\{F\}) + m_{DS}(\{F, \neg F\}) \\ &= 0.7961 \\ Pl(\{F\}) - Bel(\{F\}) &= m_{DS}(\{F, \neg F\}) = 0.0123 \\ Bel(\{F\}) &= m_{\mathrm{PCR5}}(\{F\}) = 0.7378 \\ Pl(\{F\}) &= m_{\mathrm{PCR5}}(\{F\}) \\ &\quad + m_{\mathrm{PCR5}}(\{F, \neg F\}) = 0.7453 \\ Pl(\{F\}) - Bel(\{F\}) &= m_{\mathrm{PCR5}}(\{F, \neg F\}) = 0.0075 \\ P_{DS}(\{F\}) &= m_{DS}(\{F\}) + \frac{1}{2} m_{DS}(\{F, \neg F\}) \\ &= 0.78995 \\ P_{\mathrm{PCR5}}(\{F\}) &= m_{\mathrm{PCR5}}(\{F\}) \\ &\quad + \frac{1}{2} m_{\mathrm{PCR5}}(\{F, \neg F\}) = 0.74155. \end{aligned}$$

In this example, we simply know that the mass of ignorance committed by the PCR5 rule ($m_{\mathrm{PCR5}}(F \cup \neg F) = 0.0075$) is less than that of Dempster's rule ($m_{DS}(F \cup \neg F) = 0.0123$), 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. However, when we compare the confidence level of the two cases, the maximum of pignistic probability of the PCR5 rule ($P_{\mathrm{PCR5}}(\{F\}) = 0.74155$) is less than that of Dempster's rule ($P_{DS}(\{F\}) = 0.78995$), because the PCR5 rule redistributes the partial conflicting mass to both positive and negative results of mass distributions concurrently. Thus, in the next section, we analyze the reason that the DSmT approach based on PCR5 rule is better than the DST approach based on Dempster's rule, even if the confidence level of the DST approach is higher than that of the DSmT approach.

TABLE III
EXAMPLES OF THE DEGREES OF THE BELIEF OR PROBABILITY FOR AN F SITUATION BASED ON THE NUMBERS OF ACTIVATED SENSORS

$ActivatedSensors$	$Probability$ (BNs)	P_{DS} (F)	P_{PCR5} (F)
S	0.3	0.0459	0.1637
Bp	0.19	0.0384	0.0618
S,Bp	0.39	0.2410	0.2919
Bt,R	0.46	0.3326	0.4227
S,L,H	0.45	0.2403	0.4276
S,L,Bp	0.465	0.4022	0.4344
S,L,H,Bp	0.54	0.6674	0.5773
S,L,Bt,R	0.735	0.8892	0.8601
S,L,H,Bt,R	0.81	0.9615	0.9382
S,L,H,Bp,Bt,R	0.9	0.9963	0.9963

VI. Comparison and Analysis

First, we compare the belief or probability levels of three cases: (1) BNs, (2) DST, and (3) DSmT based on the SEN. Second, the uncertainty levels of two cases: (1) DST and (2) DSmT is compared by applying three methods: 1) defined static weighting factors, 2) different static weighting factors, and 3) different discounting rates into two fusion processes. Finally, we compare the uncertainty levels of two cases: (1) DST and (2) DSmT with combining other algorithms such as the TBF having different thresholds.

A. Belief Levels of Three Cases: BNS, DST, and DSMT

We assume that $\Theta = \{Sl, F\}$ be the frame made of only two hypotheses to compare DSmT with BNs and DST. In this case, the probability theory (i.e., BNs) and the DST deal, under the assumptions on exclusivity and exhaustivity of hypotheses, with basic probability assignments (BPA) $m(.) \in [0,1]$ such that $m(Sl) + m(F) = 1$ and $m(Sl) + m(F) + m(Sl \cup F) = 1$, respectively. DSmT deals, under only assumption on exhaustivity of hypotheses, with the GBBA $m(.) \in [0,1]$ such that $m(Sl) + m(F) + m(Sl \cup F) + m(Sl \cap F) = 1$. However, we use the same underlying model [Shafer's model ($M^0(\Theta)$)] [26], which reduces the D^Θ into the 2^Θ without loss of generality by assuming exclusivity between elements of the Θ, for the sake of comparison among BNs, DST and DSmT. We assume that the numbers of activated sensors are increased based on the time progress. The "F" situation of the patient is calculated based on the time progress and the numbers of activated sensors.

Table III and Fig. 6 show the results of the confidence levels based on time progress. According to Table III, the degrees of the belief or probability level for the "F" situation of three cases are increased based on the numbers of activated sensors. When small numbers of sensors are activated, the degrees of probability level of BNs are higher than those of others. The reason is that BNs do not consider the uncertainty level of two different evidences. When four more sensors are activated, the degrees of pignistic probability level of DST are higher than those of others. The reason is that DST do not consider the conflicting mass, which increases the uncertainty level in evidential networks, of two different evidences. Based on the results of Table III and Fig. 6, the confidence level of DST is higher than others in the emergency situation of the patient when medical body sensors are activated. However, the evidential fusion based on DST has more various conflicting

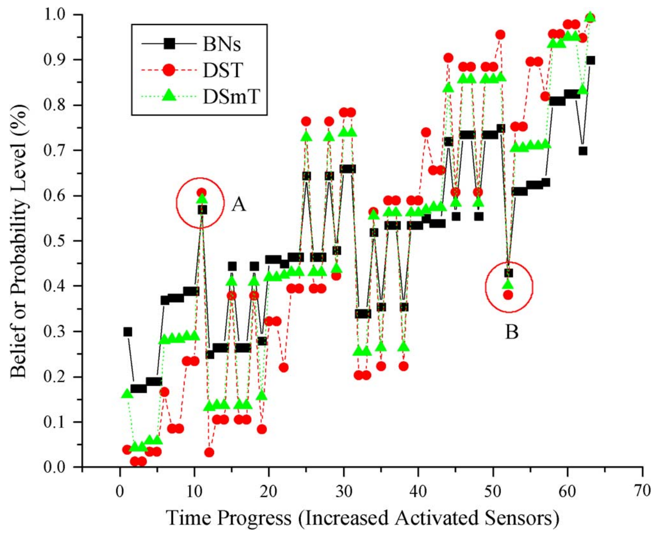


Fig. 6. Example of the belief or probability levels of three cases based on the time progress (increased activated sensors).

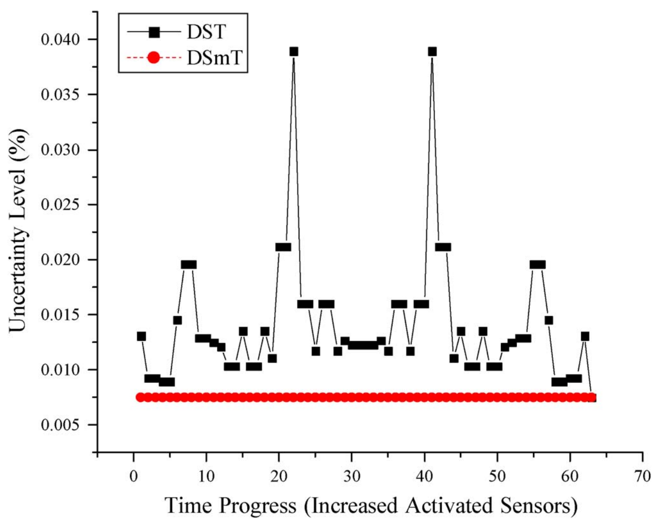


Fig. 7. Uncertainty levels of two cases based on the numbers of activated sensors and the aggregation of activated sensors.

mass in the uncertainty level compared to the DSmT approach as shown in Fig. 7. We need to reduce the conflicting mass in uncertainty level to achieve correct decision making for the situation of the patient.

In addition, according to Fig. 6, the Bel of (A) (i.e., Ps and Rs) is bigger than that of (B) (i.e., Ls, Ms, and Bps) even if the numbers of activated sensors of (A) is smaller than that of (B), since the applied weighting factors of (A) are bigger than those of (B). This shows the importance of the method to define a static weighting factors for each context attribute in evidential networks.

B. Uncertainty Levels of Two Cases: DST and DSmT

We calculate the uncertainty levels (ignorance) of two cases: (1) DST and (2) DSmT, which are used for calculating the "F" situation of the patient. We cannot calculate the uncertainty level using BNs, since BNs, which assume equality between the implication and the conditional belief [23], cannot support a certain degree α which takes a value from the interval [0, 1].

TABLE IV
APPLIED DIFFERENT STATIC WEIGHTING FACTORS

S	L	H	Bp	Bt	R
0.9	0.05	0.05	0.05	0.05	0.9
0.8	0.1	0.1	0.1	0.1	0.8
0.7	0.1	0.2	0.1	0.2	0.7
0.6	0.2	0.2	0.2	0.2	0.6
0.5	0.2	0.3	0.2	0.3	0.5
0.4	0.3	0.3	0.3	0.3	0.4
0.3	0.4	0.3	0.3	0.4	0.3
0.2	0.4	0.4	0.4	0.4	0.2
0.1	0.45	0.45	0.45	0.45	0.1

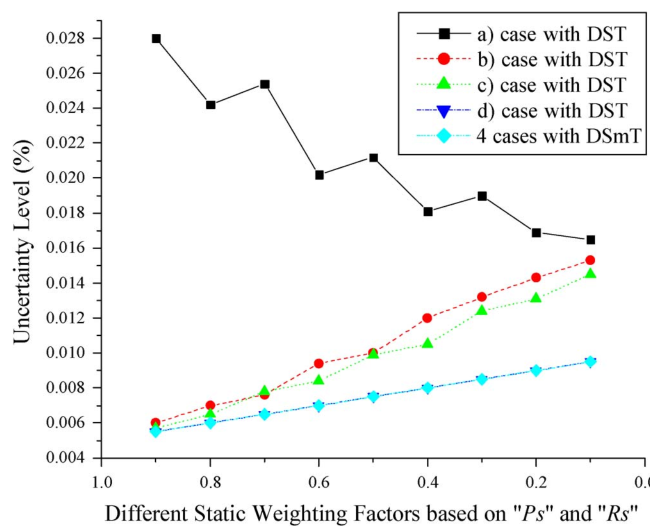


Fig. 8. Uncertainty levels of two cases based on different static weighting factors depending on the decrease of weights on Ps and Rs.

1) Comparison With the Defined Static Weighting Factors: We apply the defined static weighting factors to each context attribute, as shown in Fig. 5. The uncertainty levels of two cases based on the numbers of activated sensors are shown in Fig. 7. The degrees of uncertainty level of DSmT have constant values (i.e., 0.0075), because the PCR5 rule redistributes the total conflicting mass as equal to zero within the DSmT framework. However, the degrees of uncertainty level of DST have different values, depending on the aggregation of activated sensors, because Dempster's rule takes the total conflicting mass and redistributes it to all nonempty sets within the DST framework, even those not involved in the conflict. As shown in Fig. 7, the degrees of uncertainty level of DSmT are lower than those of DST at any time. Hence, the DSmT approach with defined static weighting factors gets better performance than the DST approach to reduce the conflicting mass in uncertain contextual information of the patient.

2) Comparison With Different Static Weighting Factors: We apply different weights to each context attribute, as shown in Table IV, to compare the uncertainty levels of two cases—DST and DSmT—based on different weighting factors. In this case, we calculate four situations: 1) Bts and Rs are not activated; 2) Ls and Bps are not activated; 3) only Bts is not activated; and 4) all sensors are activated.

Fig. 8 shows the uncertainty levels of two cases based on different weighting factors. As shown in Fig. 8, the uncertainty levels of DSmT have the same degrees for all cases, although the uncertainty levels of DST have different degrees, depending

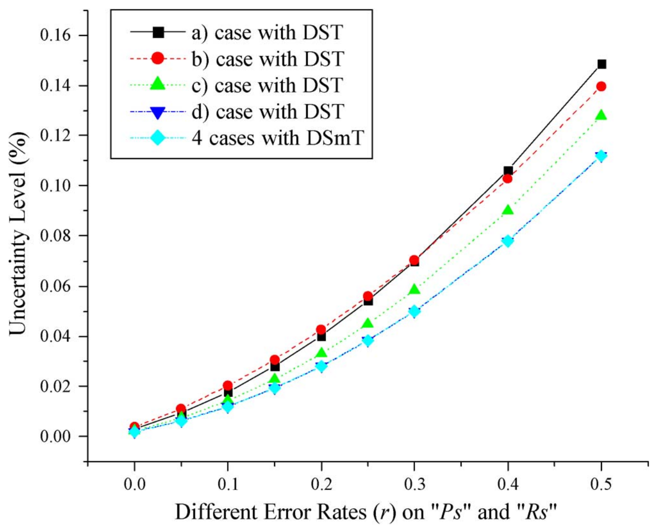


Fig. 9. Uncertainty levels of two cases based on different error rates r, depending on the increase in error rates r on Ps and Rs.

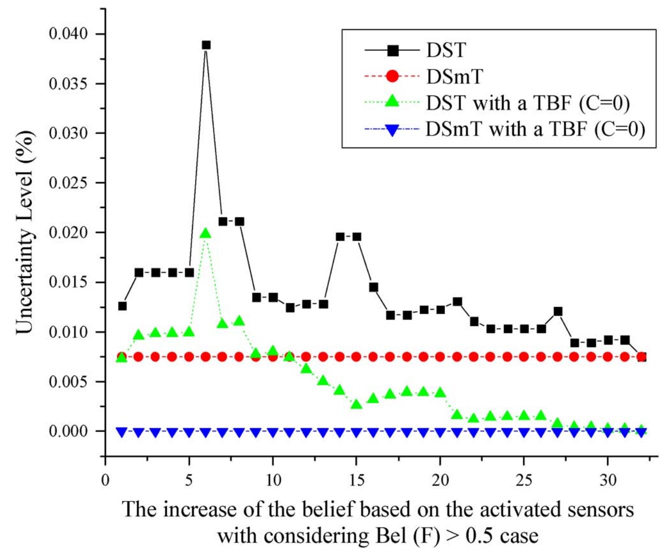


Fig. 10. Uncertainty levels of two cases when considering a TBF.

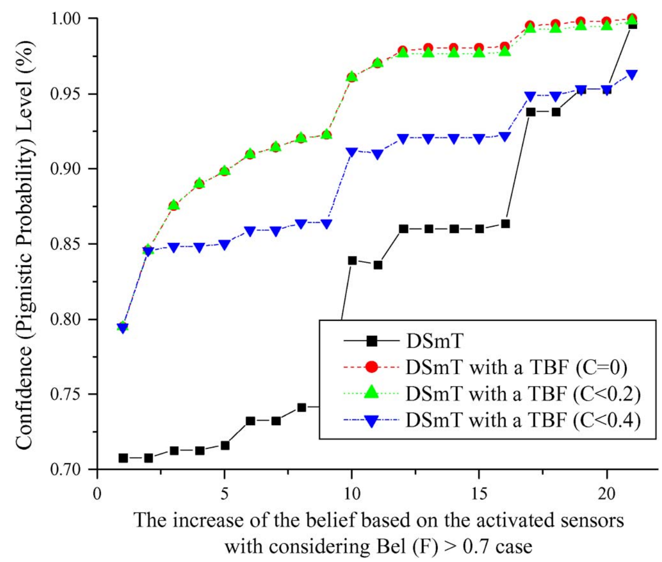


Fig. 11. Confidence (pignistic probability) levels of the DSmT approach when considering different TBF thresholds.

on the four situations. In addition, the degrees of uncertainty level of DSmT are lower than those of DST. Only when all sensors are activated will the degrees of uncertainty level of DSmT be equal to those of DST. It means that the evidential fusion based on DSmT shows a constant uncertainty level, whether a sensor reading error may happen or whether an emergency situation may progress, by redistributing the total conflicting mass only into the sets involved in the conflict and proportionally to their masses. Hence, the DSmT approach with different static weighting factors also shows better performance than the DST approach for reducing the uncertainty level of contextual information in the progress of F situation.

3) Comparison With Different Error Rates r: We apply different r, which are related to sensor's credibility, into Ps and Rs to calculate the uncertainty levels of two cases. Reducing the r on each sensor is an important factor to obtain the reliability of contextual information of the patient. We calculate four situations: 1) Bts and Bps are not activated; 2) Ps and Bts are not activated; 3) only Bps is not activated; and 4) all sensors are activated. We apply the static weighting factors to each context attribute as equal to the used values in Fig. 5. Depending on different r on Ps and Rs, the two cases show different degrees of uncertainty levels, as shown in Fig. 9. The degrees of uncertainty levels of these two cases are increased based on the increase of the r as expected. In this case, the uncertainty levels of DSmT have same degrees for all cases, although those of DST have different degrees for the four situations. Moreover, the degrees of uncertainty level of DSmT are lower than those of DST. This result also shows that the DSmT approach gets the better performance than the DST approach for reducing the uncertainty level of contextual information in the progress of an F situation.

C. Uncertainty Levels of Two Cases With the TBF

After performing SEFP within evidential networks, we apply a TBF using (9) and (14)–(16) to compare the two cases. We assume that the predefined threshold C for the conflict value C_F is equal to zero. We consider that the degree of a belief is greater than 0.5 ($Bel_F > 0.5$). As shown in Fig. 10, we can reduce the degrees of uncertainty levels of the two cases when we apply a TBF. In this case, the DSmT approach still has a better performance than the DST approach for reducing the uncertainty level of contextual information. In addition, we compare the confidence (pignistic probability) levels of the DSmT approach by applying different TBF thresholds such as $C = 0$, $C < 0.2$, and $C < 0.4$ into the $Bel_F > 0.7$ case. Depending on the selected thresholds, a conflict value C_F between prediction and measurement requires different model changes. As shown in Fig. 11, the confidence levels have different degrees based on these model evolutions. In this case, we can get a higher confidence level when we apply the $C = 0$ threshold compared to others. It means that we can get higher confidence levels when we adapt more model evolution at each time stamp. Finally, a context-reasoning method using the SEFP with the PCR5 rule and the TBF within an evidential network improves the confidence level by reducing the conflicting information in uncertainty levels of contextual information of the patient.

VII. Conclusion

To reduce the degrees of uncertainty in sensed data and in generated contexts, we have utilized SEFP with the PCR5 rule and the TBF as a context-reasoning method. We have also applied a GPT to understand uncertainty analysis in decision making. Finally, we analyze the evidential fusion approach by adapting different static weighting factors, discounting rates, and belief filter thresholds and then compare it with the DST approach. According to the results of our simulations, 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 patient.

Acknowledgment

The authors would like to thank the anonymous reviewers.

References

[1] E. Blasch, I. Kadar, J. Salerno, M. Kokar, S. Das, G. Powell, D. Corkill, and E. Ruspini, "Issues and challenges in situation assessment (level-2 fusion)," *J. Adv. Inf. Fusion*, vol. 1, no. 2, pp. 122–139, Dec. 2006.

[2] N. Bricon-Souf and C. R. Newman, "Context awareness in healthcare: A review," *Int. J. Med. Inf.*, vol. 76, no. 1, pp. 2–12, 2007.

[3] W. Dargie, "The role of probabilistic schemes in multisensor context awareness," in *Proc. 5th IEEE Int. Conf. Pervasive Comput. Commun. Workshops*, 2007, pp. 27–32.

[4] J. Dezert and F. Smarandache, *Advances and Applications of DSmT for Information Fusion*. Rehoboth, NM: Amer. Res. Press, 2004.

[5] J. Dezert and F. Smarandache, *Advances and Applications of DSmT for Information Fusion*. Rehoboth, NM: Amer. Res. Press, 2006.

[6] J. Dezert and F. Smarandache, *Advances and Applications of DSmT for Information Fusion*. Rehoboth, NM: Amer. Res. Press, 2009.

[7] J. Dezert, F. Smarandache, and M. Daniel, "The generalized pignistic transformation," in *Proc. 7th Int. Conf. Inf. Fusion*, 2004, pp. 384–391.

[8] D. L. Hall and J. Llinas, "An introduction to multisensor data fusion," *Proc. IEEE*, vol. 85, no. 1, pp. 6–23, Jan. 1997.

[9] K. Henricksen, J. Indulska, and A. Rakotonirainy, "Modeling context information in pervasive computing systems," in *Proc. 1st Int. Conf. Pervasive Comput.*, London, U.K., 2002, pp. 167–180.

[10] X. Hong, C. Nugent, M. Mulvenna, S. McClean, B. Scotney, and S. Devlin, "Evidential fusion of sensor data for activity recognition in smart homes," *Pervasive Mobile Comput.*, vol. 5, no. 3, pp. 236–252, Jun. 2008.

[11] H. Lee, J. S. Choi, and R. Elmasri, "A classification and modeling of the quality of contextual information in smart spaces," presented at the 6th IEEE PerCom Workshop CoMoRea, Galveston, TX, 2009, pp. 1–5.

[12] H. Lee, J. S. Choi, and R. Elmasri, "Sensor data fusion using DSm theory for activity recognition under uncertainty in home-based care," in *Proc. 23th IEEE AINA*, Bradford, U.K., 2009, pp. 517–524.

[13] H. Lee, K. Park, B. Lee, J. Choi, and R. Elmasri, "Issues in data fusion for healthcare monitoring," presented at the 1st ACM Int. Conf. Pervasive Technol. Related Assistive Environ., Athens, Greece, 2008.

[14] W. Liu, J. Hong, and M. McTear, "An extended framework for evidential reasoning systems," in *Proc. 2nd IEEE Int. Conf. Tools Artif. Intell.*, 1990, pp. 731–737.

[15] S. Maskell, "A Bayesian approach to fusing uncertain, imprecise and conflicting information," *Inf. Fusion*, vol. 9, no. 2, pp. 259–277, Apr. 2008.

[16] C. K. Murphy, "Combining belief functions when evidence conflicts," in *Decision Support Systems*. Amsterdam, The Netherlands: Elsevier, 2000, pp. 1–9.

[17] A. Padovitz, S. W. Loke, A. Zaslavsky, and C. Bartolini, "An approach to data fusion for context awareness," in *Proc. 5th Int. Conf. Modelling Using Context*, 2005, pp. 353–367.

[18] F. Paganelli and D. Giuli, "A context-aware service platform to support continuous care networks for home-based assistance," in *Universal Access in Human-Computer Interaction*. New York: Springer-Verlag, 2007, pp. 168–177.

[19] J. Pansiot, D. Stoyanov, D. McIlwraith, B. P. Lo, and G. Z. Yang, "Ambient and wearable sensor fusion for activity recognition in healthcare monitoring systems," in *Proc. 4th Int. Workshop Wearable Implantable Body Sensor Netw.*, 2007, vol. 13, pp. 208–212.

[20] R. Polikar, A. Topalis, D. Parikh, D. Green, J. Frymiare, J. Kounios, and C. M. Clark, "An ensemble based data fusion approach for early diagnosis of Alzheimer's disease," *Inf. Fusion*, vol. 9, no. 1, pp. 83–95, Jan. 2008.

[21] E. Ramasso, M. Rombant, and D. Pellerin, "A temporal belief filter improving human action recognition in videos," in *Proc. IEEE ICASSP*, 2006, pp. 141–144.

[22] A. Ranganathan, J. Al-Muhtadi, and R. H. Campbell, "Reasoning about uncertain contexts in pervasive computing environments," *IEEE Pervasive Comput.*, vol. 3, no. 2, pp. 62–70, Apr. 2004.

[23] B. Ristic and P. Smets, "Target identification using belief functions and implication rules," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 41, no. 3, pp. 1097–1103, Jul. 2005.

[24] G. L. Rogova, "Reliability in information fusion: Literature survey," in *Proc. 7th Int. Conf. Inf. Fusion*, 2004, pp. 1158–1165.

[25] J. Roy, "From data fusion to situation analysis," in *Proc. 4th Int. Conf. Inf. Fusion*, 2001, pp. 3–10.

[26] G. Shafer, *A Mathematical Theory of Evidence*. Princeton, NJ: Princeton Univ. Press, 1976.

[27] F. Smaradache and J. Dezert, "Information fusion based on new proportional conflict redistribution rules," in *Proc. 8th Int. Conf. Inf. Fusion*, 2005, pp. 907–914.

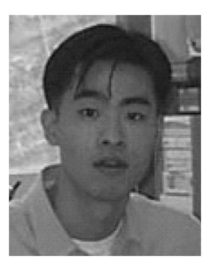
[28] P. Smets, "Data fusion in the transferable belief model," in *Proc. 3rd Int. Conf. Inf. Fusion*, 2000, pp. 21–33.

[29] P. Smets and R. Kennes, "The transfer belief model," *Artif. Intell.*, vol. 66, no. 2, pp. 191–234, Apr. 1994.

[30] H. Wu, M. Siegel, and S. Ablay, "Sensor fusion using Dempster–Shafer theory II: Static weighting and Kalman-filter-like dynamic weighting," in *Proc. 20th IEEE Instrum. Meas. Technol. Conf.*, 2003, vol. 2, pp. 907–912.

Hyun Lee (M'09) received the B.E. and M.S. degrees from Sunmoon University, Asan, Korea, in 1998 and 2002, respectively. He is currently working toward the Ph.D. degree in the Department of Computer Science and Engineering, University of Texas at Arlington.

His research interests include issues related to sensor fusion techniques and the integration of heterogeneous sensors and RFID systems for improving the reliability of contextual information in pervasive computing areas.



Jae Sung Choi received the B.A. degree in computer engineering in 2003 from Kyungsung University, Busan, Korea, and the M.S degree in computer science and engineering in 2006, from the University of Texas at Arlington, where he is currently working toward the Ph.D. degree in the Department of Computer Science and Engineering.

His research interests include performance analysis of passive UHF RFID system and object tracking and classifying in integration of RFID and WSN.

Ramez Elmasri (M'98) received the B.S. degree in electrical engineering from Alexandria University, Alexandria, Egypt, in 1972 and the M.S. and Ph.D. degrees in computer science from Stanford University, Stanford, CA, in 1980.

He is currently a Professor of computer science and engineering with the Department of Computer Science and Engineering, University of Texas at Arlington. His research interests include issues related to sensor networks (querying, indexing, energy-efficient data collection, integration with RFID, and sensor architectures), RFID, and XML (keyword-based querying, indexing, distributed XML, and caching).

Dr. Elmasri is a member of the IEEE Computer Society.